Stockholm School of Economics
Department of Finance
Master of Science in Finance
Master Thesis - Double Degree Program

Information Spillover from VIX Options to VIX Futures: the Information Content of Put-Call Ratio and Implied Volatility Skew

Giorgio Magagnotti

May 2016

Abstract:
This paper investigates the predictive power of the information content of VIX options with respect to VIX futures. Two sub-samples of variables are used in the analysis: put-call ratios of daily option volumes and spreads among implied volatilities across different moneyness levels, derived from VIX options prices. The statistical significance and the forecasting accuracy of various predictive models are back-tested through the computation of one-day ahead out-of-sample forecasts, using both expanding and rolling estimation windows. Different statistical indicators are employed to identify the best performing models. The results indicate that put-call ratio and implied volatility skew variables possess predictive power with respect to VIX futures, and their combined inclusion improves the forecasting accuracy.

Supervisor: Prof. Paolo Sodini
Key words: VIX futures, VIX options, put-call ratio, implied volatility skew

Aknowledgements

I deeply thank my supervisor Prof. Paolo Sodini for his advices, support and supervision throughout all the steps of this work.
I also owe my gratitude to Prof. Francesco Saita, for his interest in the topic, his mentoring and his patience.

a Erica

a Ivan

INDEX

INTRODUCTION

Derivative instruments play a fundamental role in the development of modern financial markets. This type of security is priced according to a non-arbitrage paradigm with respect to the underlying asset and to the other securities traded in the market. Given the relationship with the respective underlying instrument, an ever-increasing number of authors have investigated the possible presence of information spillover from one market to the other. Specifically, the focus has been the information content of derivative instruments with respect to future prices and returns of underlying assets. The main reason for information to be first incorporated and exploited in derivatives markets is the higher level of leverage achievable through them. One class of derivatives particularly affected by these dynamics are option contracts, since they are priced using inputs directly derived from the underlying securities.

In the vast body of literature that deals with the information content of options, two features have been extensively studied: the put-call ratio and the implied volatility skew. The put-call ratio is generally defined as the ratio between the volume of put and call options traded on a given day. It is both treated as an information indicator, which reflects informed trading activity in the market, and as an investor sentiment indicator. In this second instance, it is used as a contrarian indicator, where a high level of the ratio indicates a great amount of fear in the market. Whether this comes from an increased risk-aversion, more demand for insurance against market drops or just overreaction to negative shocks, determines the goodness of the indicator. The implied volatility skew comes from the asymmetry across various moneyness levels of the expected volatility for the underlying asset implied by option prices. The implied volatility skew is accounted by computing differences of implied volatilities among out-of-the-money, at-the-money and in-the-money call and put options. These volatility spreads may contain information about future prices and returns of the underlying security. The results of this body of research indicate that the information content of option markets, whether traded volumes or spreads in implied volatilities, does possess forecasting power with respect to the future dynamics of the underlying asset.

The aim of this paper is to assess the forecasting power of VIX options on VIX futures, using both classes of variables and combining them together. The innovative aspects of this work with respect to the existing literature are that we combine trading volumes and implied volatility spreads of VIX options and we employ them to predict the future dynamics of VIX futures. Previous researches either used the two groups of variables separately or tried to assess their forecasting power with respect to equity indexes. The study is conducted on daily data from January 3rd, 2007 to August 31st, 2015. The dependent variable, on which the forecasting power is assessed, is the one-day ahead 1st generic VIX future, $VixF_{(t+1)}$. Different versions of put-call ratio and implied volatility skew variables are constructed and their statistically significance checked through univariate and multivariate regressions. Put-call ratios can be computed both using raw or smoothed daily volumes data, and including only observations on options with a specific maturity ranges. The implied volatility skew can be accounted using spreads on different moneyness levels within the same type of option contract or considering differences between call and put options skew. We conduct an in-sample analysis to identify the most significant independent variables and then combine them to construct various predictive models. In the last part of the paper, we recursively compute the one-day ahead out-of-sample forecast, using both expanding and rolling estimation windows, and the statistical performance of each model is assessed through different statistical indicators. The results of this work prove that put-call ratio and implied volatility skew variables have statistically significant predictive power with respect to VIX futures. Predictive models that include these variables, perform better than the benchmark model.

The paper is organized as follows. Section 2 includes an overview on the VIX index, VIX futures and VIX options, while section 3 summarizes the existing relevant literature. Section 4 contains the empirical analysis, including the construction of the variables, the in-sample and the out-of-sample analysis. Section 5 reports the main result, limitations and extensions. Section 6 concludes.

2. VIX INDEX, FUTURES AND OPTIONS

Academics and practitioners realized long ago that stochastic volatility is a fundamental risk factor, which affects both the pricing and hedging of many financial securities. The necessity to take into account stochastic volatility in assessing and hedging portfolio returns required the creation of a reference index. In 1993, the Chicago Board Options Exchange (CBOE) introduced the Volatility Index (VIX). It was originally designed to measure the market's expectation of 30-day volatility implied by at-the-money S&P 100 option prices. It was updated in 2003, and it is since based on the SPX. The majority of investors look at the VIX index because it provides useful information about the current market mood, which can in turn be used to predict potential market swings. Given its strong negative correlation to the SPX, it is also a very effective risk management tool in equity portfolio management. However, other market participants take positions in VIX derivatives instruments with the sole purpose to speculate on the future direction of the market. VIX futures contracts were introduced on March, 24th 2004 and VIX options came along two years later, on February, 24th 2006. VIX derivatives are among the most actively traded contracts at CBOE, because of their ability to hedge the risks of positions in the SPX index or to heavily speculate on it.

2.1 VIX index

The VIX index, is an up-to-the-minute market estimate of the expected volatility of the SPX index over the next 30 days. It is computed using real-time prices of options on the SPX index traded during regular trading hours. The procedure used to compute the VIX is articulated in three main steps.

1. Selection of the options contracts to be included in the computation:

The near-term and next-term call and put options to be used in the calculation are selected. They are the options expiring in the first and second SPX contracts months.

2. Calculation of the variance of near-term and next-term options

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT}\, Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$$

where:

- $\sigma = \frac{VIX}{100}$
- T = Time to expiration
- F = Forward index level desired from index option prices
- K_0 = First strike below the forward index level F
- K_i = Strike price of the i[th] out-of-the-money option: a call if $K_i > K_0$, a put if $K_i < K_0$ or both call and put if $K_i = K_0$
- ΔK_i = Interval between strike prices
- R = Risk-free interest rate to expiration derived from the bond equivalent yield of the U.S. T-bill maturing with the closest expiration date
- $Q(K_i)$ = The midpoint of the bid-ask spread for each option with strike K_i

3. Calculation of the VIX index:

The index is computed as the square root of the 30-day weighted average of the variances derived in early in the procedure

$$\mathrm{VIX} = \sqrt{\left\{T_1\sigma_1^2\left[\frac{N_{T_2}-N_{30}}{N_{T_2}-N_{T_1}}\right] + T_2\sigma_2^2\left[\frac{N_{30}-N_{T_1}}{N_{T_2}-N_{T_1}}\right]\right\} \times \frac{N_{365}}{N_{30}}} \times 100$$

where:

- T_1 and T_2 are the time to expiration of the near-term and next-term VIX options measured in calendar days scaled by minutes. This is done in order to obtain the same precision option and volatility traders commonly use.

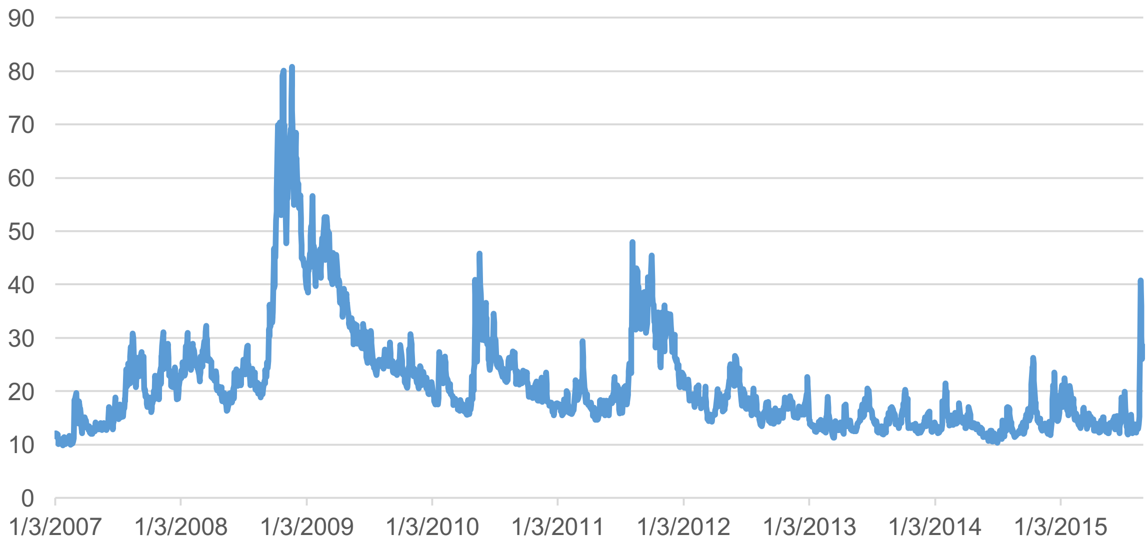
  N_{T_1} is the number of minutes before the settlement of the near-term VIX options
- N_{T_2} is the number of minutes before the settlement of the next-term VIX options
- N_{30} is the number of minutes in 30 days
- N_{365} is the number of minutes in 365 days
- σ_1^2 and σ_2^2 are the variances of the near-term and next-term VIX options

Figure 1 shows the trend of the VIX index during the observation sample used in our analysis, from January, 3[rd] 2007 to August,31[st] 2015. The index peaked during the financial crisis on November, 20[th] 2008 and touched its low on January, 24[th] 2007.

Table 1: Summary statistics for VIX index

	2007	2008	2009	2010	2011	2012	2013	2014	2015
Max	31,09	80,86	56,65	45,79	48,00	26,66	20,49	26,25	40,74
Mean	17,54	32,69	31,48	22,55	24,20	17,80	14,23	14,18	15,57
Min	9,89	16,30	19,47	15,45	14,62	13,45	11,30	10,32	11,95
St.Dev.	5,35	16,35	9,06	5,26	8,12	2,54	1,74	2,63	4,09

Figure 1: VIX index



2.2 VIX futures

On March, 24th 2004 VIX futures were introduced by the CBOE. They are standard future contracts with cash settlement to a special opening quotation (SOQ) of VIX. The price of VIX futures represents the expected spot 30-day implied volatility for the SPX on the expiration date of the specific contract. Prices of VIX futures contracts could be either higher or lower than the underlying VIX index. This is due to the fact that market expectations for the future volatility may vary for each different expiration. The pricing relationship between VIX futures and VIX index is unique. Almost all futures contracts are structured on a "cost of carry" relationship, by which futures mirror the performance of the underlying asset. With the ability to replicate the performance, there could be an arbitrage if the future is mispriced relatively to its underlying asset. Arbitrageurs take advantage of such mispricings when they occur, which directly causes futures contracts to trade within a narrow range close to the price of the underlying instrument. On the contrary, there is no such possibility as to replicate the performance of the VIX index in the same way as other financial products. The formula to compute the VIX index takes into account the mid-point between bid and offer of SPX option contracts, and this does not necessarily represent a price where VIX futures contracts may be readily traded. This results in the inability of traders to quickly trade SPX options to lock in a 30-day implied volatility versus the VIX index. Given the impossibility to arbitrage between VIX index and VIX futures, there is no arbitrage-value relationship between the two. VIX futures trading hours have been extended to nearly 24 hours a day five days a week starting June 2014 and from July, 23rd 2015 VIX weekly futures began trading at CBOE Futures Exchange. Below are reported the summary statistics for the first three generic VIX futures (those expiring in one, two and three months respectively) and their cross-correlation with the VIX index. It should be noticed how:

- the correlation of VIX futures with VIX index decreases for longer maturities, which is consistent with the idea that the dependence of the future level of expected volatility with respect to the VIX index, is smaller the longer the time horizon.

- the mean value increases for longer maturities, while the standard deviation decreases. This reflects not only the well-documented overestimation of implied volatility over longer horizons, but also the lower variability, direct consequence of the mean-reversion feature of the volatility itself.

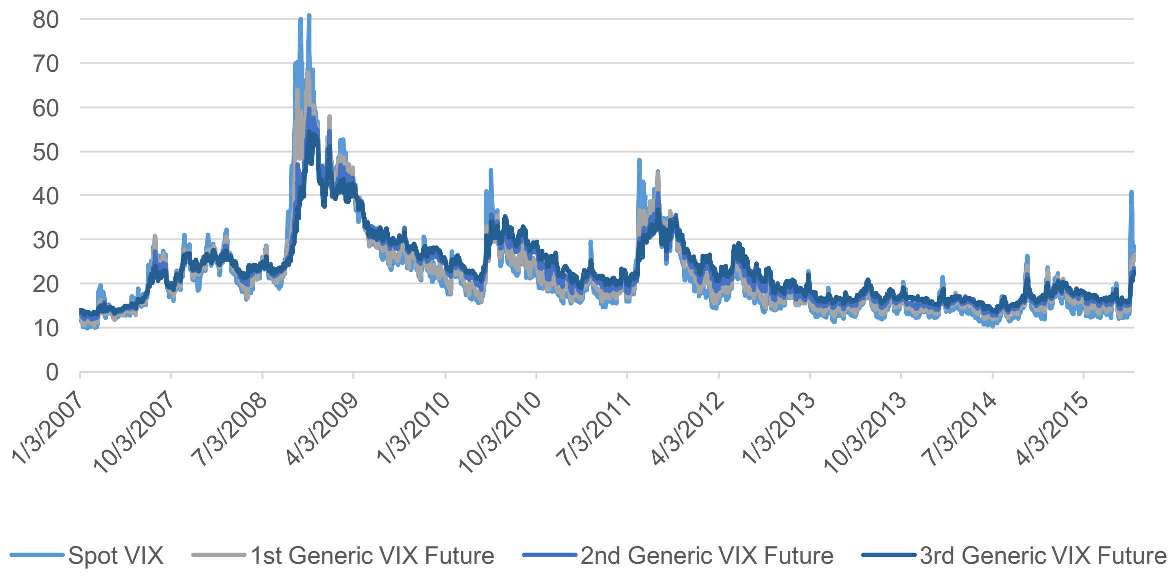
Table 2: Summary statistics for VIX index and VIX futures

	VIX Index	1st Generic VIX Future	2nd Generic VIX Future	3rd Generic VIX Future
Max	80,86	67,95	59,77	54,67
Mean	21,36	21,81	22,55	23,00
Min	9,89	10,43	11,89	12,83
# Obs	2181	2181	2181	2181
St.Dev.	10,16	9,17	8,12	7,42

Table 3: Correlations for VIX index and VIX futures

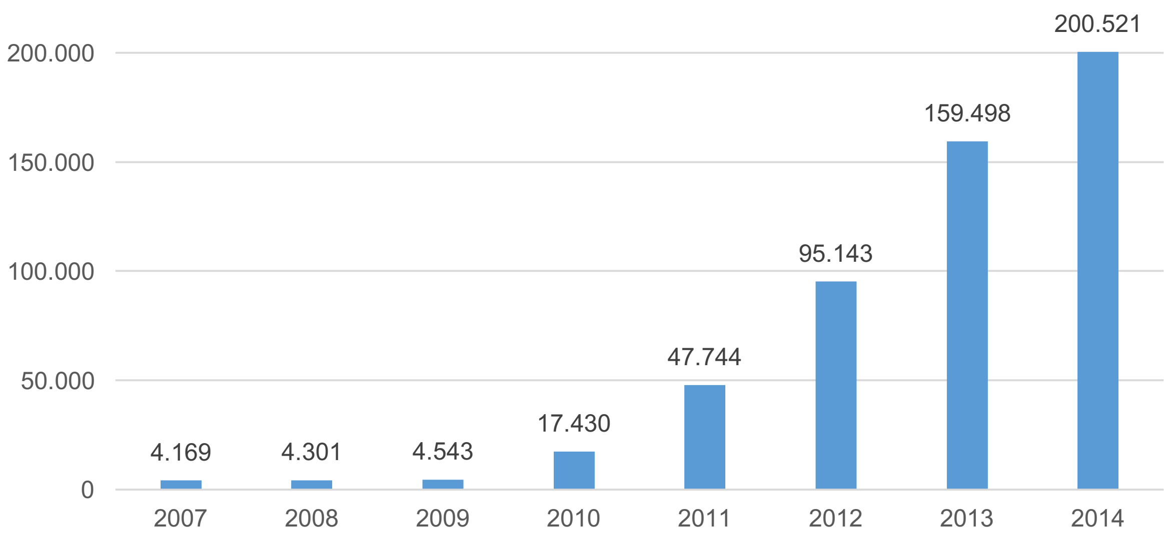
	VIX Index	1st Generic VIX Future	2nd Generic VIX Future	3rd Generic VIX Future
VIX Index	1,000	0,982	0,939	0,906
1st Generic VIX Future	0,982	1,000	0,979	0,954
2nd Generic VIX Future	0,939	0,979	1,000	0,992
3rd Generic VIX Future	0,906	0,954	0,992	1,000

Figure 2: VIX index and 1st - 2nd - 3rd VIX futures



VIX futures quickly became popular among investors and volatility traders. The average daily traded volume experienced an exponential growth over the years, topping 200,000 contracts traded daily in 2014.

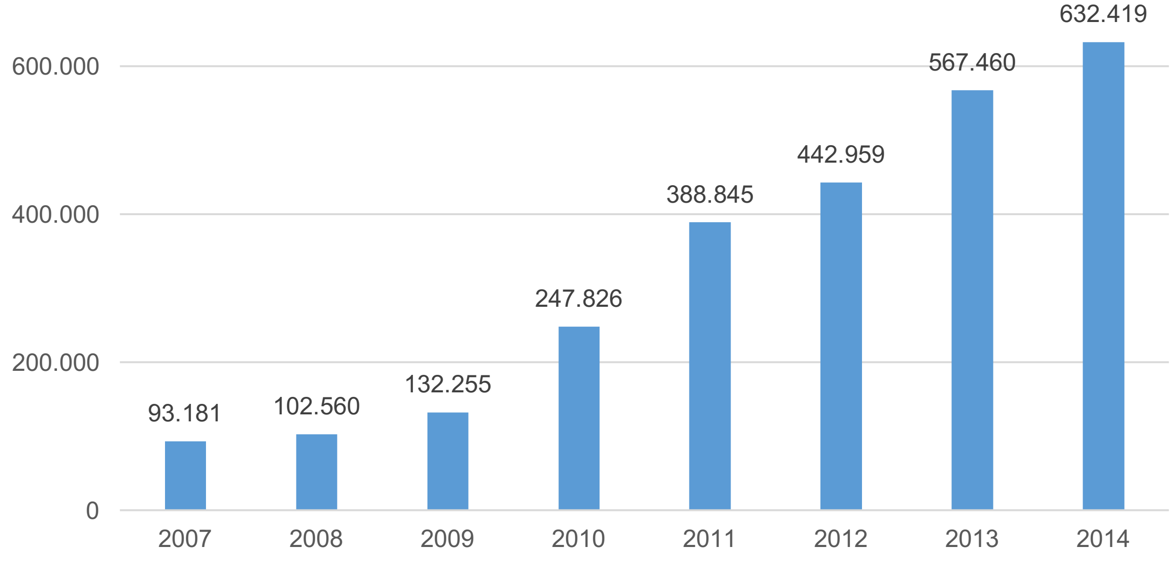
Figure 3: Average daily volume of VIX futures



2.3 VIX options

On February, 24th 2006 VIX options began trading on the CBOE. The European style option contracts are written on the VIX future with the corresponding maturity and have cash settlement. Given the specific computation procedure of the VIX index, VIX options expire on the Wednesday 30 days before the third Friday of the calendar month after the expiring month. The settlement value is a special opening quotations (SOQ) of VIX. VIX options liquidity is mainly concentrated on short maturities, with 65% of contracts having less than 45 days to maturity (figure 10). The average daily traded volume experienced a six-fold increase from 2007 to 2014 (figure 4). VIX option implied volatility skew is uniquely shaped, with out-of-the-money call options showing higher implied volatilities than in-the money call options. The implied volatility skew is thus upward sloping, opposite from equity indexes options. Implied volatilities are also generally higher for call than for put options. Both features are due to the particular nature of the VIX and the hedging purposes VIX options are traded for. Given the great complexity of this product and high risks associated, VIX options are mainly traded by professionals and institutional investors.

Figure 4: Average daily volume of VIX options



3. LITERATURE REVIEW

Equity instrument and option contracts trade in different markets, in distinct locations and at different times. However, despite the presence of the above mentioned physical constraints, the two markets are highly integrated between themselves, and information revealed in one of them should be readily transmitted and incorporated in the other one. Many researches focused on the behavior of informed investors, who should theoretically first go to option markets, in order to exploit the greater leverage derivatives offer. A growing stream of literature focuses on proving the existence of a direct link between information embedded in option markets and the future dynamics of the underlying assets. The findings suggest that information spillover may be present from the option markets to the equity markets. Two classes of information have been commonly studied and used in literature: the first one uses the information contained in the volume of options traded and the ratio between the volumes of put and call options. The second group includes information related to deviations from the put-call parity and the shape of skew of the implied volatility. The following sections give an overview of the relevant literature with respect to these topics. The last part will review the literature regarding the relation between VIX index and VIX futures, given the focus of this work.

3.1 Option volume and put-call ratio

Simon and Wigging (2001) examined the predictive power of different popular investors' sentiment measures in respect to future returns of SPX futures contract over three different time horizons (10-20-30 days) from January 1989 to June 1999. The measures the authors used in their analysis are the put-call ratio, the volatility index (VIX) and the trading index (TRIN). They demonstrated that these variables do have statistically significant predictive power and that they can be used as contrarian indicators. This implies that periods of extreme high level of fear among investors in the market provide convenient and remunerative buying opportunities. The last part of the paper tests out-of-sample trading strategies, implemented during the second time period of the observation sample. The results suggest that risk-adjusted profits could be realized by buying SPX futures when fear indicators spike at high levels. Pan and Poteshman (2006) found solid evidence in their work that options trading volume contains information about future dynamics of the underlying assets. They computed put-call ratios from option volume of transactions initiated by buyers in order to open new positions. Stocks possessing low put-call ratios outperform stocks with high put-call ratios by more than 0.40% on the next day and more than 1% over the next week. Dividing option signals used in the data analysis into parts that are publicly and non-publicly available, they found that the root of the predictability derives from nonpublic information and is not caused by market inefficiencies. The predictability is higher for stocks with greater concentration of informed traders and for options with a higher degree of leverage. Bandopadhyaya and Jones (2008) used in their work two investor sentiment measures computed and made publicly available by the CBOE daily. This is an ideal feature since it makes possible to retrieve and use them for everyone, both academics and practitioners. The two variables considered are the put-call ratio and the VIX index. The authors used daily data from January, 2nd 2004 to April, 11th 2006 for their analysis and discovered that the put-call ratio does possess better explanatory power than the VIX in explaining returns for the SPX index, even after including different control variables.

3.2 Implied volatility skew and deviations from put-call parity

Doran, Peterson and Tarrant (2007) studied the information content of the shape of the implied volatility skew and assessed its forecasting power with respect to market dynamics. The analysis includes all options on the S&P 100 from 1984 to 2006, and the results confirmed that the implied volatility skew derived from actually traded option prices has predictive power in forecasting market movements. Furthermore, the authors tested if this statistical significance is economically exploitable and found that it is not. The findings are more robust in the short-term for out-of-the-money put options. This is consistent with the paradigm of investors' aversion to large market drops. The predictive power also tends to decrease with longer options maturities. Xing, Zhang and Zhao (2010) also assessed the cross-sectional predictive power of the shape of the implied volatility skew with respect to future stock returns. They found that stocks that have a heavily pronounced skew do underperform stocks with less inclined volatility skew by almost 11% per year on a risk-adjusted basis. The predictability remains statistically significant up to six months. The results of the work are also coherent with the paradigm that informed traders, who possess negative news are more likely to trade out-of-the-money put options, and that equity markets do not quickly incorporate all the information embedded in option markets. Doran and Krieger

(2010) studied how information contained in the implied volatility skew affects future returns of the underlying assets. The results show that future returns can be related to the spreads between call and put implied volatilities. Spreads between at-the-money options have been computed to account for the middle of the skew, while the left side has been defined by differences between out-of-the-money and at-the-money puts. The work shows that many option-based measures of the implied volatility skew do posses strong predictive power in forecasting the future dynamics of the underlying assets. The authors also indicated that information is contained in different parts of the implied volatility skew, particularly in two sections: in the middle, given by the difference between at-the-money call and put volatility, and on the left-hand side of the skew, between the out-of-the-money and at-the-money puts. Cremers and Weinbaum (2010) provided strong evidences in their work that deviations from the put-call parity incorporate statistically significant information with respect to future returns of the underlying assets. They computed the differences in implied volatilities, also known as volatility spread, for pairs of call and put options on the same underlying stock, with equal strike price and time to expiration, to account for the above mentioned deviations. Since single name option contracts may be exercised before maturity (American style options), spreads among implied volatilities only represent deviations from a theoretical pricing model and do not directly imply the presence of arbitrage opportunities. However, they can be viewed as a way to pin down price pressure signals in the derivatives market. These signals incorporate statistically significant information, which are economically exploitable. A long-short portfolio in equities with comparatively expensive calls versus comparatively expensive puts gains a risk-adjusted abnormal return of 0.50% per week. The degree of predictability is greater when option liquidity is high and stock liquidity low, whereas there is low predictability when option liquidity is low and stock liquidity is high. The authors also discovered that, first, option prices are far more likely not to adhere to the put-call parity relation when the underlying stocks face high information risk, and second, that the degree of predictability declines overtime. Chung, Tsai, Wang and Weng (2011) empirically investigate the information content of SPX index and VIX options, under the assumption that they both have forecasting power with respect to returns, volatility, and density for the SPX index. The results of the paper show that the information content implied in the two option markets is not identical or redundant. Predictive models for the SPX index are statistically improved by including information recovered from the VIX options. These findings are robust to different measures of realized volatility and methods of density evaluation. An, Ang, Bali and Cakici (2014), found that stocks presenting high spikes in call (put) implied volatilities during the previous month do generate high (low) future returns. They implemented and back-tested a long-short strategy based on decile portfolios sorted by past values of implied volatilities; this position produced an average return of 1% per month and the spread showed signs of persistence up to 6 months. In the paper also provides evidence about how the cross section of equity returns possesses predictive power with respect to option implied volatilities. Stocks with large returns in the previous periods exhibit substantial increases in call and put options implied volatility during the next 30 days. Despite being most significant over one month horizon, this predictability persists up to six months. The high-frequency data used in this study proves that both option and equity markets react quickly to external news, and that using high-frequency data, options and stocks seem to be fairly priced in relation to each other.

3.3 VIX index and VIX futures

The temporal relationship between the VIX index and the VIX futures is affected by peculiar features. Above all, the VIX index is not tradable since it is a forecasted implied volatility derived from SPX options. Given the large amount of contracts that are used in its calculations and the continuous rebalancing, it is not feasible to replicate the VIX index through the basket of options form which it is derived. For all these reasons, the classic cost of carry relationship is absent between spot and future prices. Another feature that largely impacts the spot-future relation, is the mean-reverting property of the volatility (i.e. a large increase in the current volatility will be followed by a decrease in the future, and vice versa). The VIX index represents the next 30 days implied volatility. The VIX future represents the expected volatility for the 30-day period in 30 days. If the option market forecasts a volatility decrease during the next 30 days, the VIX spot will decrease. However, the price of the VIX future will not decrease to the same extent, since the implied volatility will tend to revert to its long-run mean. Shu and Zhang (2011) analyzed the price-discovery function and information efficiency of the VIX futures market. Using a linear Engle-Granger cointegration test with an error correction mechanism (ECM) they found that VIX futures prices lead spot VIX index during the full time sample. This implies that VIX futures have some kind of price-discovery function. Subsequently, a nonlinear Granger test was introduced, given the fact that the traditional linear test fails in detecting nonlinear casual relations. As a result, a bi-directional causality between VIX spot and VIX futures prices has been discovered, suggesting that both instruments' prices react to new information contemporaneously. These causality tests between the VIX spot and VIX futures do provide an incidental comparison of the relative allure of using the SPX options or VIX futures as hedging tools. Both SPX put options and VIX futures can be used to hedge downside risks. On one hand, if investors prefer to trade options, the VIX spot derived from option quotes will lead VIX futures; on the other hand, if investors are far more attracted by VIX futures, those will lead VIX spot. Estimated quarterly parameters are not statistically different from zero, thus producing further evidence in support of the information efficiency of the VIX futures market. Karagiannis (2014) analyzed the lead-lag relation between the VIX futures and VIX index price changes. The front month VIX futures contract is used as proxy for the future market. In the paper a Johansen cointegration approach with a vector error correction model and Granger causality analysis are employed. The results indicate that VIX futures lead spot VIX index, thus impling that VIX futures market do have a greater role in price discovery. Frijns, Tourani-Rad and Webb (2014) studied the intraday dynamics of the VIX index and VIX futures market for a period spanning from January 2, 2008 to December 31, 2012. The authors applied a vector autoregressive (VAR) model using daily data, and detected evidence of causality from the VIX futures to the VIX spot. However, calibrating a vector auto regressive model with ultra-high frequency data, they found strong evidence of bi-directional Granger causality between the VIX and the VIX futures. Overall, the causality effect seems to be stronger from the VIX futures to the VIX index than the other way around. Conducting impulse response functions and variance decompositions analysis further confirm the dominance of the VIX futures. The work also points out how this causality increased over the sample period, whereas the reverse causality decreased. These findings suggest that the VIX futures have become increasingly more important in the pricing of volatility. They further document how VIX futures dominate the VIX spot in greater measure on days with negative returns, and on days with high values of the VIX spot itself. This suggest that investors may use VIX futures to hedge their positions rather than trading in the SPX index options on those days.

4. EMPIRICAL ANALYSIS

The analysis we conduct in this work aims to assess the information content of VIX options with respect to VIX futures. Particularly, it focuses on the information contained in the put-call ratio of options trading volume and in the implied volatility skew. The general form of the models used in the paper is thus:

$$VixF_{(t+1)} = \alpha + + \beta_i[PCR\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)} + \varepsilon_{(t)}$$

* *β_i with i = 1,..,N where N is the total number of variables - valid for all the analysis*

Variables contained in the put-call ratio group have been constructed using daily trading volume data, while variables of implied volatility skew have been computed through a linear interpolation process. After constructing the independent variables, we proceed with an in-sample analysis. We run a number of univariate and multivariate regressions in order to find the most significant variables to include in the predictive models. We first consider all possible combinations of the independent variables and then use three (stepwise, swapwise and combinatorial) additional automatic variable selection procedures to find the most significant relations. In the next part of the paper, we use the most significant independent variables to construct different predictive models. We then proceed with a recursive back-testing exercise where we constantly evaluate the one-day out-of-sample forecast of each predictive model in order to find the most accurate ones. The performance evaluation is done through several different statistical indicators, in order to be complete and avoid any bias that the use of a particular indicator may cause. The predictive models have been estimated both using an expanding and a rolling estimation window.

4.1 Data

The dataset used in our analysis comes from OptionMetrics WRDS (Wharton Research Data Services) and includes data on all VIX options (CUSIP: 12497K). We decided not to include data from 2006 given the low market liquidity and the high dispersion of the observations. The sample used in the analysis thus ranges from 01/01/2007 to 31/08/2015. The total number of observations is 727,951, which decrease to 257,788 after deleting all entries with daily trading volume equal to 0. Moneyness levels have been computed as the ratio between the strike price of the option contract and the level of the 1st generic VIX future (VX1). Figure 5 reports the total options trading volume per year, while figure 6 shows the yearly percentages. The six-fold increase from 2007 to 2014 is an evidence of the importance that this derivative instrument gained during recent years. Figure 7 and 8 report the number of implied volatility observations per year in absolute and percentage terms, respectively.

Figure 5: Options trading volume per year

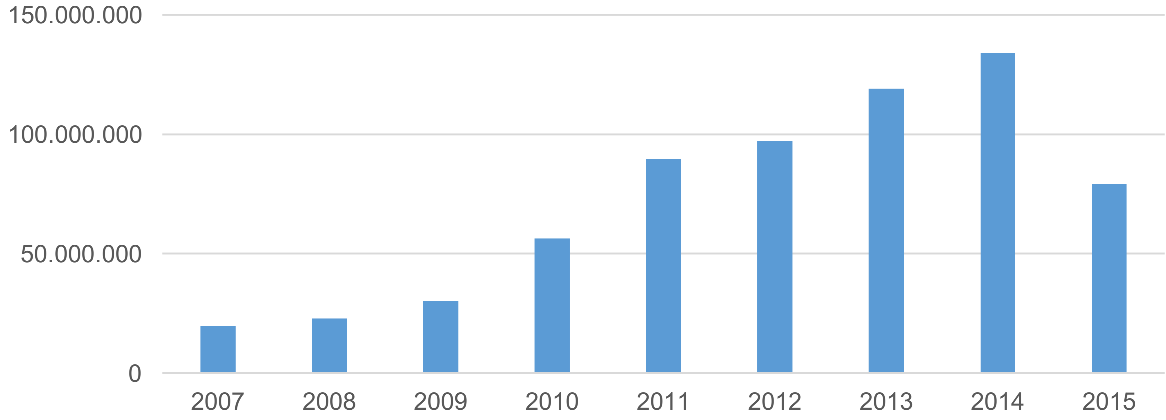


Figure 6: Percentage of options trading volume per year

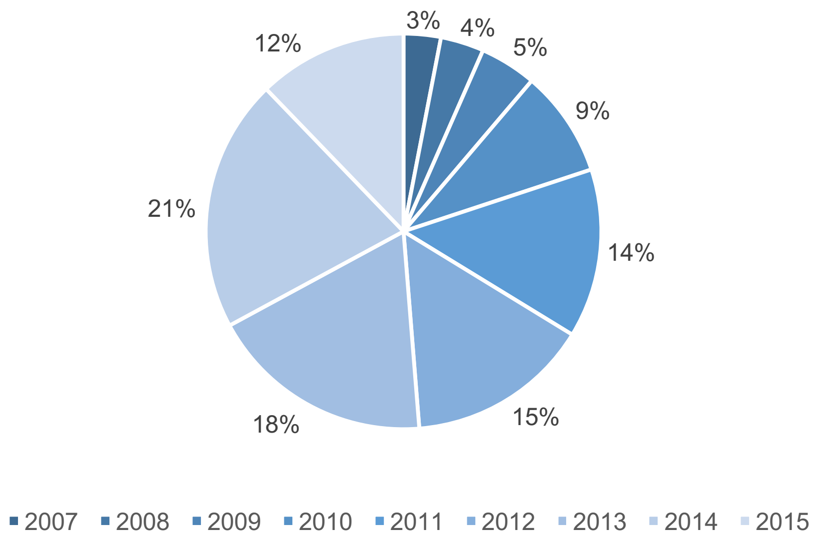


Figure 7: Implied volatility observations per year

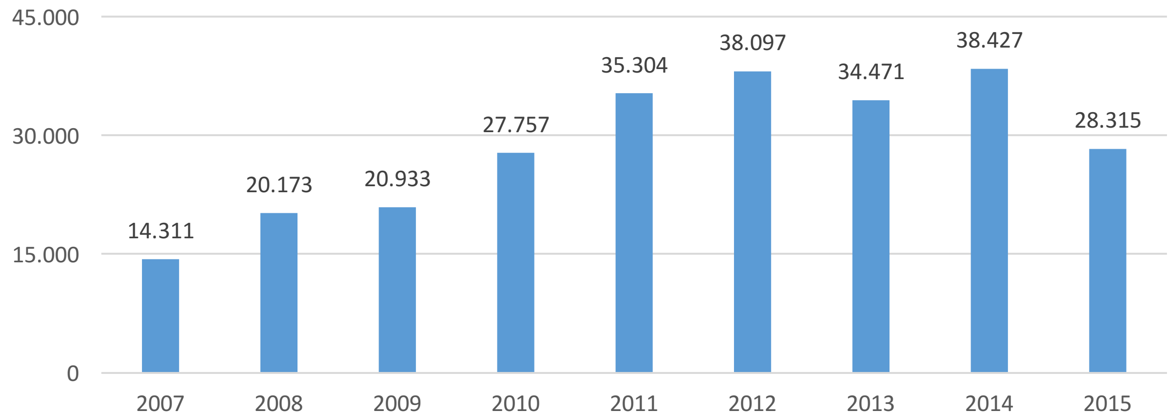
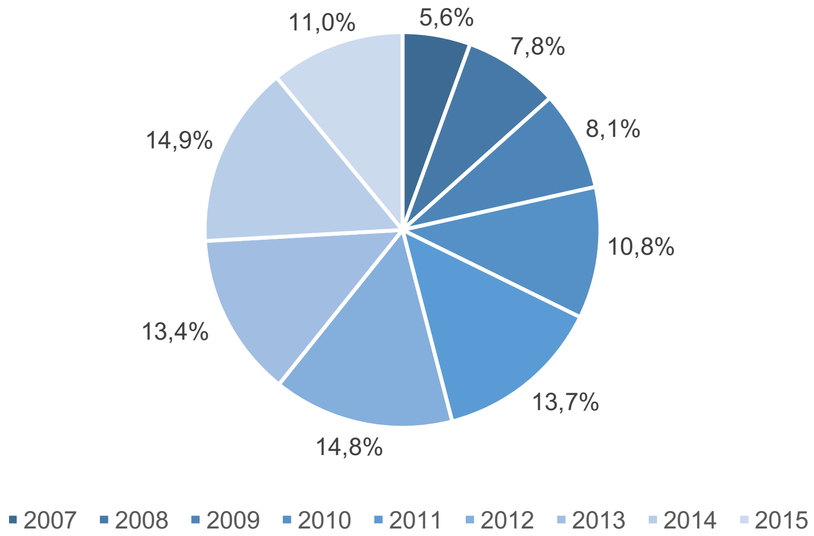


Figure 8: Percentage of implied volatility observations per year



4.1.1 VIX futures

Given that the goal of this work is to investigate the information content of VIX options with respect to VIX futures, we decided to use the one-day-ahead 1st generic VIX future (VX1) as dependent variable. We perform a unit root test and the time series appears to be integrated of order one, I(1), thus being non-stationary. In order to avoid spurious regression results we decided to include the current 1st generic VIX future level in the independent variables of the model. Given the existing literature on the relation between VIX index and VIX futures, we also included the current VIX index level as independent variable.

4.1.2 Put-call ratio

The put-call ratio is defined as the ratio of the volume of put options over the volume of call options traded in a given day. Generally, it is computed using all the contracts traded in each given day, including all the expirations and strike prices. In this work, a more sophisticated approach is followed. Various put-call ratios according to different maturity buckets have been calculated. This is because different pieces of information may be contained in ratios constructed starting from different maturity ranges. Investors may take position VIX options having different maturities according to specific purposes. This may cause different kind of information to be contained in different maturity bucket. Moreover, ratios can be calculated by using raw totals of call and put options volumes or, by first averaging the totals over a number of days, and then dividing the averaged values. In the first case the classic put-call ratio is obtained, while following the second method, a smoothed put-call ratio is calculated. We then decided to compute the following put-call ratios in order to be detect every possible piece of information contained in this variable:

1. Unsmoothed all days to maturity (PCRALL) - put-call ratio computed starting from raw daily volumes and including all option contracts
2. Unsmoothed 1-30 days to maturity (PCR130) - put-call ratio computed starting from raw daily volumes and including option contracts with expiration date between 1 and 30 days
3. Unsmoothed 1-60 days to maturity (PCR160) - put-call ratio computed starting from raw daily volumes and including option contracts with expiration date between 1 and 60 days
4. Unsmoothed 15-45 days to maturity (PCR1545) - put-call ratio computed starting from raw daily volumes and including option contracts with expiration date between 15 and 45 days
5. Smoothed all days to maturity (PCRALLSM) - put-call ratio computed starting from averaging daily volumes over 5 days and including all option contracts
6. Smoothed 1-30 days to maturity (PCR130SM) - put-call ratio computed starting from averaging daily volumes over 5 days and including option contracts with expiration date between 1 and 30 days
7. Smoothed 1-60 days to maturity (PCR160SM) - put-call ratio computed starting from averaging daily volumes over 5 days and including option contracts with expiration date between 1 and 60 days

8. Smoothed 15-45 days to maturity (PCR1545SM) - put-call ratio computed starting from averaging daily volumes over 5 days and including option contracts with expiration date between 15 and 45 days

Table 4 and 5 report summary statistics and correlation for the eight put-call ratio variables, while figure 9 and 10 indicate the absolute and percentage values of traded option volumes across different maturity buckets. Figure 11 and 12 summarize the frequency distribution of unsmoothed and smoothed put-call ratios. Given the particular nature of VIX index and the main purpose of VIX options (hedging against spikes in volatility by buying call options), we expect the frequency distribution to be skewed to the left. The results are consistent, with almost 30% of observed put-call ratios for both sub-samples are in the interval 0,3-0,5.

Table 4: Summary statistics for put-call ratios

	PCRALL	PCR 130	PCR 3160	PCR 160	PCR 1545	PCR ALLSM	PCR 130SM	PCR 160SM	PCR 1545SM
Max	4,08	10,27	18,07	4,63	18,07	1,86	10,27	2,17	3,17
Mean	0,58	0,74	0,64	0,60	0,60	0,53	0,66	0,54	0,53
Min	0,02	0,01	0,00	0,02	0,01	0,07	0,05	0,06	0,05
# Obs	2181	2181	2181	2181	2181	2177	2177	2177	2177
St.Dev.	0,44	0,79	0,91	0,48	0,73	0,25	0,55	0,28	0,33

Table 5: Correlations among put-call ratios

	PCR 130	PCR 1545	PCR 160	PCR ALL	PCR 130SM	PCR 1545SM	PCR 160SM	PCR ALLSM
PCR130	1,000	0,314	0,708	0,529	0,608	0,285	0,469	0,414
PCR1545	0,314	1,000	0,659	0,594	0,270	0,473	0,369	0,359
PCR160	0,708	0,659	1,000	0,818	0,533	0,507	0,591	0,548
PCRALL	0,529	0,594	0,818	1,000	0,414	0,444	0,500	0,575
PCR130SM	0,608	0,270	0,533	0,414	1,000	0,582	0,833	0,720
PCR1545SM	0,285	0,473	0,507	0,444	0,582	1,000	0,798	0,741
PCR160SM	0,469	0,369	0,591	0,500	0,833	0,798	1,000	0,894
PCRALLSM	0,414	0,359	0,548	0,575	0,720	0,741	0,894	1,000

Figure 9: Options volume per maturity buckets

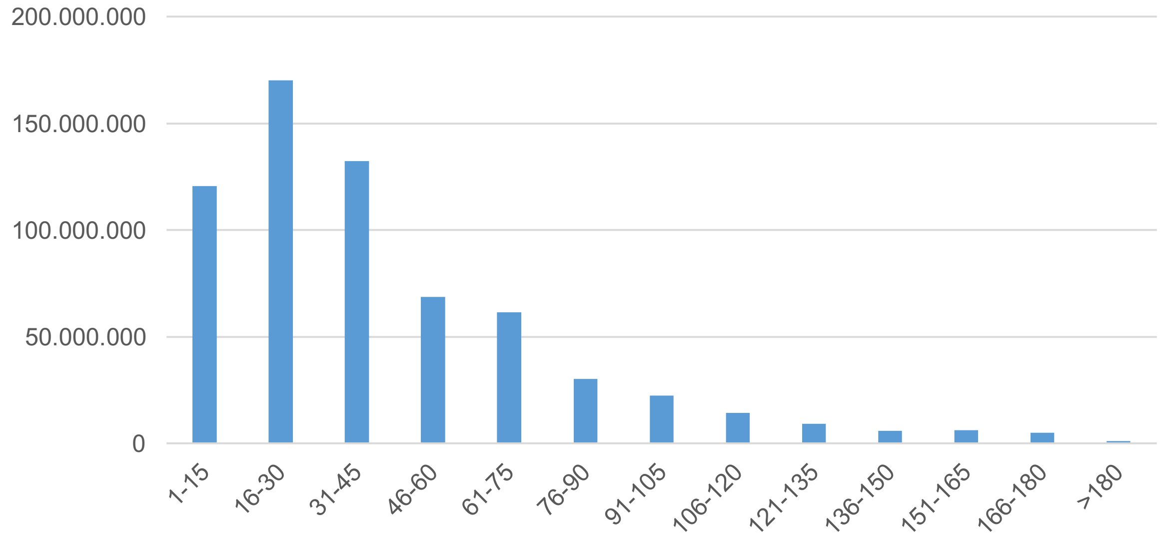


Figure 10: Percentage of options volume per maturity buckets

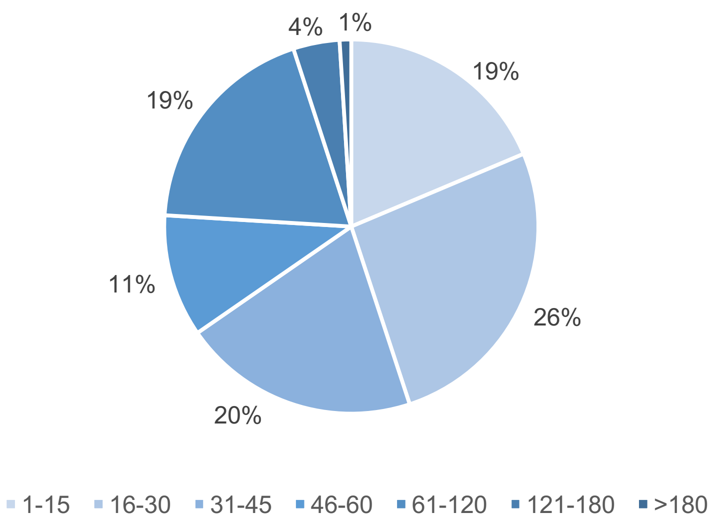


Figure 11: Put-call ratios frequency distributions

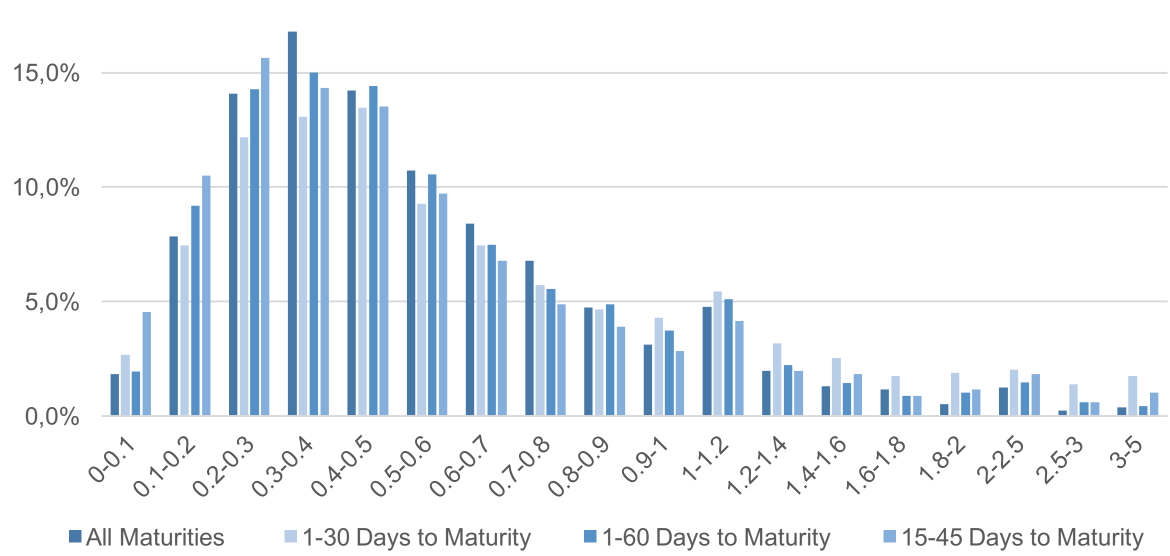
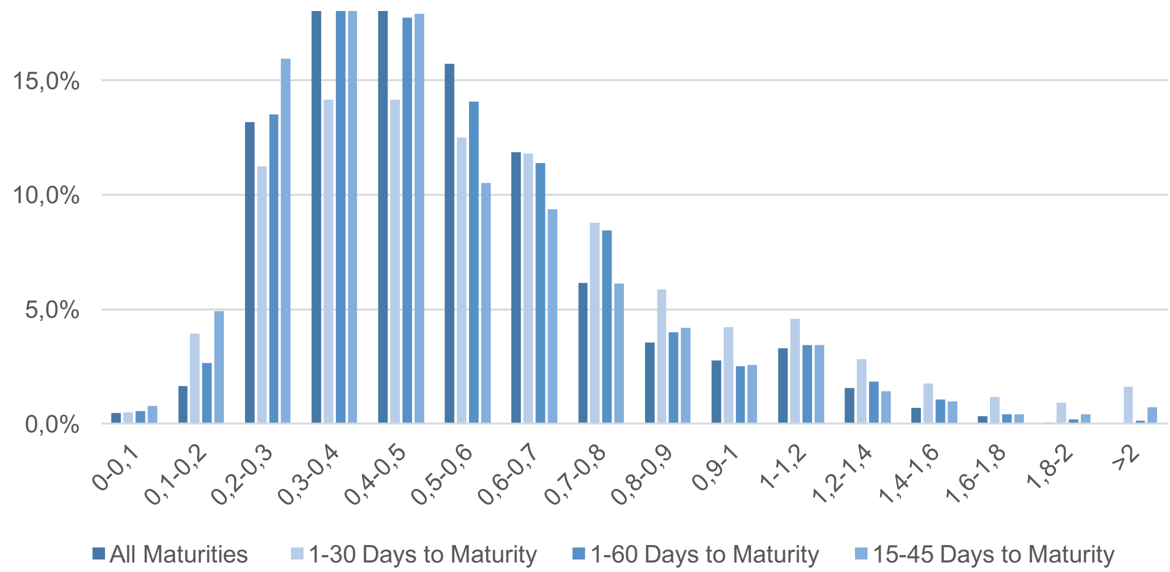


Figure 12: Smoothed put-call ratios frequency distribution



4.1.3 Implied volatility skew

The variables accounting for the implied volatility skew have been computed starting from Doran and Krieger (2010). In the work, five measures have been used.

- Above-Minus-Below (AMB) = $([(IV_{c,OTM}+IV_{p,ITM})-(IV_{c,ITM}+IV_{p,OTM})]/2)$; it is the difference between the implied volatilities of the options pairs with moneyness above and below 100%, respectively and accounts for the tails of the volatility skew
- Call-Out-Minus-At (COMA) = $IV_{c,OTM}$ - $IV_{c,ATM}$; it is the difference between the implied volatility of out and at-the-money call options and accounts for the right and middle side of the volatility skew for calls
- Put-Out-Minus-At (POMA) = $IV_{p,OTM}$ - $IV_{p,ATM}$; it is the difference between the implied volatility of out and at-the-money put options and accounts for the left and middle side of the volatility skew for puts
- Cremers and Weinbaum (CW) = $IV_{c,ATM}$ - $IV_{p,ATM}$; it is the difference between the implied volatility of at-the-money call and put options and accounts for the middle of the volatility skew
- Zing, Zhang and Zhao (ZZX) = $IV_{c,OTM}$ - $IV_{p,ATM}$; it is the difference between the implied volatility of out-of-the-money call and at-the-money put options and accounts for the section across the right call volatility skew and middle put volatility skew

Two of the variables can be combined to form another one of them, as COMA+CW=ZZX. In order to account for the positive skew of implied volatility in VIX options, ($IV_{c,OTM} > IV_{c,ATM} > IV_{p,ATM} > IV_{p,OTM}$), we used modified versions of the above. The variables considered in our analysis are therefore:

1. Above-Minus-Below (AMB) = $([(IV_{c,OTM}+IV_{p,ITM})-(IV_{c,ITM}+IV_{p,OTM})]/2)$
2. Call-Out-Minus-At (COMA) = $IV_{c,OTM} - IV_{c,ATM}$
3. Put-At-Minus-Out (PAMO) = $IV_{p,ATM} - IV_{p,OTM}$
4. Call-At-Minus-Put-At (CAPA) = $IV_{c,ATM} - IV_{p,\ ATM}$
5. Call-Out-Minus-Put-At (COPA) = $IV_{c,OTM} - IV_{p,ATM}$

As in Doran and Krieger COMA+CW=ZZX, we have that COMA+CAPA=COPA. In order to compute the measures, consistent values for OTM-ATM-ITM call and put options were needed. Those values have been derived by linearly interpolating five constant values of moneyness:

- 80% for deep OTM put and deep ITM call options
- 90% for OTM put and ITM call options
- 100% for ATM put and call options
- 110% for ITM put and OTM call options
- 120% for deep ITM put and deep OTM call options

The linear interpolation has been computed using the first value above and the first value below the desired levels of moneyness. When this was not feasible for the lack of observations on either sides, the two values, either above or below, have been used. In all other cases, no values have been interpolated. Since we decided to use as dependent variable the 1st generic VIX future, a constant interpolation at 30 days has also been computed. This has been done by linearly interpolating the implied volatilities corresponding to the two closest maturities to 30 days, one above and one below. All five selected variables have been computed using both “deep” OTM-ITM (80%-120%) and OTM-ITM (90%-110%) options. We decided to proceed in this way in order to be as accurate as possible in measuring the variations in the skew of the implied volatility. As a result, a total of nine variables has been constructed, since Call-At-Minus-Put-At (CAPA) is computed using only ATM options.

1. Deep-Above-Below (DAMB) = $([(IV_{c,120\%}+IV_{p,120\%})-(IV_{c,80\%}+IV_{p,80\%})]/2)$
2. Above-Minus-Below (AMB) = $([(IV_{c,110\%}+IV_{p,110\%})-(IV_{c,90\%}+IV_{p,90\%})]/2)$
3. Deep-Call-Out-Minus-At (DCOMA) = $IV_{c,120\%} - IV_{c,100\%}$
4. Call-Out-Minus-At (COMA) = $IV_{c,110\%} - IV_{c,100\%}$
5. Deep-Put-At-Minus-Out (DPAMO) = $IV_{p,100\%} - IV_{p,80\%}$
6. Put-At-Minus-Out (PAMO) = $IV_{p,100\%} - IV_{p,90\%}$
7. Call-At-Minus-Put-At (CAPA) = $IV_{c,100\%} - IV_{p,100\%}$
8. Deep-Call-Out-Minus-Put-At (DCOPA) = $IV_{c,120\%} - IV_{p,100\%}$
9. Call-Out-Minus-Put-At (COPA) = $IV_{c,110\%} - IV_{p,100\%}$

Table 6: Summary statistics for implied volatility skew variables

	DAMB	AMB	DCOMA	COMA	DPAMO	PAMO	CAPA	DCOPA	COPA
Max	0,79	0,42	0,35	0,19	0,57	0,28	0,34	0,45	0,39
Mean	0,35	0,19	0,17	0,09	0,18	0,09	0,00	0,16	0,09
Min	-0,41	-0,26	-0,17	-0,18	-0,14	-0,07	-0,16	-0,07	-0,06
# Obs	2181	2181	2181	2181	2181	2181	2181	2181	2181
St.Dev.	0,14	0,08	0,06	0,04	0,09	0,04	0,02	0,06	0,04

Table 7: Correlations implied volatility skew variables

	DAMB	AMB	DCOMA	COMA	DPAMO	PAMO	CAPA	DCOPA	COPA
DAMB	1,000	0,971	0,885	0,885	0,894	0,906	-0,181	0,815	0,710
AMB	0,971	1,000	0,910	0,924	0,865	0,925	-0,144	0,854	0,770
DCOMA	0,885	0,910	1,000	0,960	0,711	0,781	-0,186	0,928	0,777
COMA	0,885	0,924	0,960	1,000	0,729	0,796	-0,215	0,877	0,796
DPAMO	0,894	0,865	0,711	0,729	1,000	0,936	-0,094	0,674	0,619
PAMO	0,906	0,925	0,781	0,796	0,936	1,000	-0,113	0,737	0,670
CAPA	-0,181	-0,144	-0,186	-0,215	-0,094	-0,113	1,000	0,193	0,420
DCOPA	0,815	0,854	0,928	0,877	0,674	0,737	0,193	1,000	0,935
COPA	0,710	0,770	0,777	0,796	0,619	0,670	0,420	0,935	1,000

4.2 In-sample analysis

4.2.1 Methodology

To identify the most explicative and relevant variables to use in the out-of-sample analysis, multivariate regressions are estimated and the significance of each coefficient is assessed. We both tested VIX index and 1st generic VIX future for stationarity. Running an Augmented Dickey-Fuller test on both time series, the null hypothesis of unit root cannot be rejected at 1% for neither of them (Panel 1, Panel 2). In the test, a trend and a constant have been included. The results do not change if only a constant or neither a constant and a trend are included. Augmented Dickey-Fuller tests have been run on the first differences for both VIX index and 1st generic VIX future. The null hypothesis of unit is rejected at 1% for both of them (Panel 3, Panel 4). Even though both variables are integrated of order one, I(1), we decided to use models in levels instead of differences because the two variables are cointegrated (Panel 5), and the series of residuals is stationary. Therefore, there is no danger of having spurious regressions. We included the VIX future lagged as well as the VIX index lagged in the independent variables, in order to avoid the omitted variable bias. We decided not to use an error correction model (ECM) since models in levels are more easily tractable and the forecasting results will not substantially change. Given all the above, the following base model has been constructed:

$$VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)}$$

The base model proves to be a good fit with both coefficients highly significant (Panel 6). The residuals are tested for serial correlation using both a correlogram (Panel 7) and a LM serial correlation test (Panel 8). Both tests confirm the presence of serial autocorrelation among residuals. Furthermore, through a White test the presence of heteroskedasticity is detected (Panel 9). The base model is therefore re-estimated using HAC (Newey-West) as covariance method in the OLS estimation. This does not change the value of the estimated parameters but adjust the standard errors and t-statistics accordingly (Panel 10). This is the base model to which put-call ratio and implied volatility skew variables groups will be added, in order to find the most relevant ones.

$$VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i [PCR\ variables]_{(t)} + \beta_i [Skew\ variables]_{(t)}$$

The four groups of independent variables are the following:

Table 8: Independent variables

Put-call ratios	Smoothed put-call ratios	Implied volatility skew	Deep implied volatility skew
PCRALL	PCRALLSM	AMB	DAMB
PCR130	PCR130SM	COMA	DCOMA
PCR160	PCR160SM	PAMO	DPAMO
PCR1545	PCR1545SM	CAPA	CAPA
		COPA	DCOPA

As a first step in our analysis, we add each group of variables to the base model and evaluate the statistical significance of the coefficients of each variable. Given the fact that COMA+CAPA=COPA and DCOMA+CAPA=DCOPA, the groups of implied volatility skew are further divided into two subgroups each, one including CAPA and the other COPA and DCOPA, respectively. This procedure is followed in order to avoid problems of collinearity among regressors. The following six multivariate regressions are then estimated.

1. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)}$ (Panel 11)
2. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)}$ (Panel 12)
3. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i[Skew\ variables\text{-}ex\ CAPA]_{(t)}$ (Panel 13)
4. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i[Skew\ variables\text{-}ex\ COPA]_{(t)}$ (Panel 14)
5. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i[Deep\text{-}Skew\ variables\text{-}ex\ CAPA]_{(t)}$ (Panel 15)
6. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i[Deep\text{-}Skew\ variables\text{-}ex\ DCOPA]_{(t)}$ (Panel 16)

In the regression models with PCR and PCRSM variables, options Total Volume has been added as control variable. Confronting CAPA versus COPA/DCOPA, the presence of the first variable improves the significance of the other coefficients (especially for COMA and DCOMA). Therefore, only the variable CAPA has been employed in the analysis from this point onward, dropping COPA and DCOPA. The next step is combining the remaining variable groups, evaluating the first pass regression results and then proceeding to eliminate all the not statistically significant variables, until the final regression model contains only variables with significant coefficients. We start from the following four regression models:

1. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 17)
2. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Deep\ Skew\ variables]_{(t)}$ (Panel 18)
3. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 19)
4. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Deep\text{-}Skew\ variables]_{(t)}$ (Panel 20)

We eliminate the least significant independent variables and re-estimate each regression model with the independent variables left. The process continues until all the remaining coefficients are statistically significant. The resulting final regression models are explicitly reported below.

1. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)}+ \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$ (Panel 21)
2. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)}+ \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta iDCOMA_{(t)} + \beta_i CAPA_{(t)}$ (Panel 22)
3. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)}+ \beta_i PCR160SM_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$ (Panel 23)
4. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)}+ \beta_i PCR160SM_{(t)} + \beta iDCOMA_{(t)} + \beta_i CAPA_{(t)}$ (Panel 24)

In addition, other three methods of estimation have been used to find the most significant independent variables. We employed three automatic variable selection procedures. The stepwise-forward method begins with no additional independent variables in the model, then proceeds to add the regressor with the lowest p-value among those pre-specified. Then the variable with the next lowest p-value is added. At this point, both added variables are checked against the backwards p-value criterion. If a regressor has a p-value higher than the specified threshold, it is removed from the estimation. Once all the removal steps have been computed for all the independent variables, the next regressor is added. For each successive step of the procedure, every previously added variable is tested again against the backwards threshold and possibly removed. The stepwise-forwards procedure stops when the smallest p-value of the regressors not yet added is higher than the established forwards stopping threshold. The swapwise method begins with no additional regressors in the model, then proceeds to add the variable that maximizes the resulting regression R^2. The regressor that brings the greatest increase in the R^2 is then included. For each couple of variables added, they are compared individually with all regressors not yet included, and it is calculated whether the R^2 could improve if an inside variable is swapped with an outside one. If this improvement is feasible, then the inside regressor is replaced by the outside one. If there are more swaps that could possibly increase the R^2, the swap that yields the greatest improvement is made. After setting the target number of regressors, the combinatorial method evaluates each possible combination of these variables, and identifies the combination that yields the highest R^2 in the regression using the specified regressors. Differently from the stepwise-forward and swapwise methods, this method evaluates every possible combination of variables, thus making it the most computational intensive among the three. With a great number of potential regressors, the combinatorial procedure may take quite a long time to estimate the final regression model. In each of the three estimation methods, $VixF_{(t)}$ and $VixS_{(t)}$ are always included in the regression model. For swapwise and combinatorial procedure the number of regressors to be included is five. Each of the three methods has been used to compute the set of four equations obtainable combining all the variables groups (PCR, PCRSM, SKEW, DEEP-SKEW).

- Stepwise:

1. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 25)
2. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Deep\ Skew\ variables]_{(t)}$ (Panel 26)
3. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 27)
4. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Deep\text{-}Skew\ variables]_{(t)}$ (Panel 28)

- Swapwise:

5. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 29)
6. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Deep\ Skew\ variables]_{(t)}$ (Panel 30)
7. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 31)
8. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Deep\text{-}Skew\ variables]_{(t)}$ (Panel 32)

- Combinatorial:

9. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 33)
10. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCR\ variables]_{(t)} + \beta_i[Deep\ Skew\ variables]_{(t)}$ (Panel 34)
11. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Skew\ variables]_{(t)}$ (Panel 35)
12. $VixF_{(t+1)} = \alpha+\beta_i VixF_{(t)}+\beta_i VixS_{(t)} + \beta_i[PCRSM\ variables]_{(t)} + \beta_i[Deep\text{-}Skew\ variables]_{(t)}$ (Panel 36)

4.2.2 Results

We analyze the results of all the regressions obtained using the above four procedures and we investigate the statistical significance of each independent variable numerous times in different models. We select the most relevant independent variables to be used in the construction of predictive models for the out-of-sample analysis:

- PCRALL
- PCR130
- DCOMA = $IV_{c,120\%} - IV_{c,100\%}$
- COMA = $IV_{c,110\%} - IV_{c,100\%}$
- DPAMO = $IV_{p,100\%} - IV_{p,80\%}$
- PAMO = $IV_{p,100\%} - IV_{p,90\%}$
- CAPA = $IV_{c,100\%} - IV_{p,100\%}$

The results are in line with what we expected. For what the put-call ratio variables concern, we found that the most significant variables are the ratios constructed using all available options (PCRALL) and using only options with 1 to 30 days to maturity (PCR130). In the first case, information from total daily traded volumes gets incorporated, while in the second variable only short term signals are detected, which we expected to contain valuable information with respect to the first maturing (near-term) VIX future. Furthermore, put-call ratio computed using raw total daily traded volumes perform better than those computed using smoothed volumes. This is a sensible since through the smoothing process we loose day-specific information contained in daily volumes, thus affecting the exploitable information content of this variable. On the other hand, the results for the implied volatility skew variables are consistent too. The selected variables reflect the whole section of the skew. DCOMA and COMA account for the right side of the skew, while DPAMO and PAMO stand for the left side. CAPA controls for the spread between the skews of call and put options. Moreover, skew variables computed with "deep" moneyness levels (80% and 120%) are found to be comparatively less significant than variables calculated with less extreme moneyness levels (90% and 110%).

4.3 Out-of-sample analysis

4.3.1 Methodology

In the out-of-sample analysis we evaluate and compare the one-day-ahead forecasts obtained by twenty different predictive models (Panel 37), constructed using the relevant independent variables found in the in-sample analysis.

1. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)}$
2. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)}$
3. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCRALL_{(t)}$
4. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)}$
5. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$
6. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i DCOMA_{(t)} + \beta_i CAPA_{(t)}$
7. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PAMO_{(t)} + \beta_i CAPA_{(t)}$
8. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i DPAMO_{(t)} + \beta_i CAPA_{(t)}$
9. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$
10. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i DCOMA_{(t)} + \beta_i CAPA_{(t)}$
11. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PAMO_{(t)} + \beta_i CAPA_{(t)}$

12. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i DPAMO_{(t)} + \beta_i CAPA_{(t)}$
13. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCRALL_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$
14. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCRALL_{(t)} + \beta_i DCOMA_{(t)} + \beta_i CAPA_{(t)}$
15. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCRALL_{(t)} + \beta_i PAMO_{(t)} + \beta_i CAPA_{(t)}$
16. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCRALL_{(t)} + \beta_i DPAMO_{(t)} + \beta_i CAPA_{(t)}$
17. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$
18. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta_i DCOMA_{(t)} + \beta_i CAPA_{(t)}$
19. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta_i PAMO_{(t)} + \beta_i CAPA_{(t)}$
20. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta_i DPAMO_{(t)} + \beta_i CAPA_{(t)}$

For all the models, one-day ahead out-of-sample forecasts, using both expanding and rolling estimation window, are computed. The expanding estimation window method takes as initial sample the period that spans from 03/01/2007 to 30/12/2011. The one-day ahead forecast and its standard error for 03/01/2012 are calculated and stored. The estimation sample is then expanded to include the actual observation of 03/01/2012. Subsequently, a new model is estimated on the sample 03/01/2007 to 03/01/2012 and the one-day ahead forecast with its standard error are computed for 04/01/2012. This procedure continues until the one-day ahead forecast and the associated standard error for 31/08/2015 are calculated. The rolling window method takes as initial sample a period of 1260 days (five years of daily data) that spans from 03/01/2007 to 30/12/2011. The one-day ahead forecast and its standard error for 03/01/2012 are calculated and stored. The estimation sample is then rolled one day forward, from 04/01/2007 to 03/01/2012. Subsequently, a new model is estimated on this sample and the one-day ahead forecast with its standard error are computed for 04/01/2012. This procedure continues until the one-day ahead forecast and the associated standard error for 31/08/2015 are calculated.

4.3.2 Results

In order to evaluate the out-of-sample statistical performance of the models, the following statistical indicators have been computed for each model:

- Mean absolute error (MAE):

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|y_t - \widehat{y}_t|$$

which represents the average of the absolute differences between actual and forecasted values.

- Mean absolute percentage error (MAPE):

$$\text{MAPE} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}\left|\frac{\mathrm{y_t}-\widehat{\mathrm{y_t}}}{Y_t}\right|$$

which represents the average of the absolute differences in percentage between actual and forecasted values.

- Root mean squared prediction error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}(\mathrm{y_t}-\hat{\mathrm{y}}_\mathrm{t})^2}$$

which represents the sample standard deviation of the differences between actual and forecasted values. RMSE aggregates the magnitude of errors in forecasts for different times into a single measure of predictive power accuracy. It is a good way to compare forecasting errors of different models for a specific variable, but not among different variables, since it is scale-dependent.

- Theil-U statistic:

$$\text{Theil-U} = \sqrt{\frac{\sum_{\mathrm{t}=1}^{\mathrm{T}-1}\left(\frac{\widehat{\mathrm{Y_{t+1}}}-\mathrm{Y_{t+1}}}{\mathrm{Y_t}}\right)^2}{\sum_{\mathrm{t}=1}^{\mathrm{T}-1}\left(\frac{\mathrm{Y_{t+1}}-\mathrm{Y_t}}{\mathrm{Y_t}}\right)^2}}$$

where $\widehat{Y_{t+1}}$ is the value of the forecast at time t+1, while Y_t and Y_{t+1} are the actual values of the variable at time t and t+1, respectively. Theil-U statistic is a measure of relative accuracy and it squares the deviations giving more weight to large errors.
The interpretation of this statistic is as follows:

  - Less than 100%: The forecasting technique is better than guessing
  - Equal to 100%: The forecasting technique is about as good as guessing
  - More than 100%: The forecasting technique is worse than guessing

- Mean Correct Prediction of Direction of Change (MCPDC):

This statistical indicator indicates the frequency the model predicts a change in sign in the forecasted variable corresponding to the one the actual observation experienced. This advantages of this measures are twofold. First, there is no the sign related bias typical of RMSE. In addition, it is directly linked to trading profits, which usually rely on correct predictions of direction for price changes.

- Theil-Inequality coefficient:

$$\text{Theil-I} = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t - \widehat{Y_t})^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\widehat{Y_t})^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t)^2}}$$

The value of this performance statistics is always between 0 and 1 given the way it is computed. The interpretation is as follows:

- If Theil-I coefficient is equal to 0, then $Y_t = \widehat{Y_t}$ for all forecasts and it means that there is a perfect fit
- If Theil-I coefficient is equal to 1, then the predictive performance is as inaccurate as it possibly could be

Theil-I coefficient may be rescaled and decomposed into three proportions of inequality: bias, variance and covariance. Bias proportion is an indicator of systematic error. The closer the bias proportion to 0, the better it is. A high value of bias proportion suggests a systematic over or under prediction. Variance proportion reflects the ability of the predicted values to replicate degree of variability in the variable forecasted. If the value of variance proportion is high, then the actual series has considerably fluctuated whereas the predicted ones has not. Covariance-proportion accounts for the unsystematic error. The closer the covariance proportion to 1, the better it is.

Table 8 and Table 9 report the values of performance statistics for all models using an expanding and a rolling estimation window, respectively. The three best performing models according to each statistic have been selected and the results are the same for the two estimation window methods:

17. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$
18. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i PCRALL_{(t)} + \beta_i DCOMA_{(t)} + \beta_i CAPA_{(t)}$
9. $VixF_{(t+1)} = \alpha + \beta_i VixF_{(t)} + \beta_i VixS_{(t)} + \beta_i PCR130_{(t)} + \beta_i COMA_{(t)} + \beta_i CAPA_{(t)}$

The findings are consistent with the economic intuition. Both put-call ratios do have predictive power, but PCR130 does perform better than PCRALL. This can be related to the fact that it only contains short-term contracts (with time to maturity between 1 and 30 days), which are supposedly more closely related to the dynamics of the near-term VIX future. Among implied volatility skew variables, the most significant are COMA and CAPA. COMA represents the right section of the skew of call options and reflects the effect of the large demand for protection against implied volatility spikes.

CAPA represents the spread between at-the-money call and put implied volatilities and also reflects the greater demand for call options in order to hedge implied volatility upward jumps.

Table 9: Performance statistics for predictive models with expanding estimation window

	MAE	MAPE	RMSE	Theil-U	MCPDC	Theil-I	Bias	Variance	Covariance
Model 1	0,66059	3,910%	0,94295	99,094%	50,65%	0,02844	1,336%	0,160%	98,504%
Model 2	0,56501	3,341%	0,83703	87,843%	53,48%	0,02526	0,785%	0,026%	99,189%
Model 3	0,65168	3,857%	0,93138	98,065%	51,09%	0,02810	1,175%	0,241%	98,584%
Model 4	0,56270	3,323%	0,83220	87,093%	54,02%	0,02512	0,873%	0,000%	99,127%
Model 5	0,60617	3,559%	0,89194	93,337%	55,33%	0,02696	0,061%	0,054%	99,886%
Model 6	0,60444	3,550%	0,88469	92,796%	55,98%	0,02677	0,043%	0,250%	99,707%
Model 7	0,62776	3,713%	0,90901	95,442%	53,04%	0,02743	0,926%	0,040%	99,034%
Model 8	0,63520	3,755%	0,91722	96,146%	52,28%	0,02766	1,502%	0,149%	98,349%
Model 9	**0,52286**	**3,083%**	0,79085	**83,018%**	59,46%	0,02392	0,000%	0,656%	99,344%
Model 10	0,52347	3,089%	**0,79017**	83,115%	**59,67%**	**0,02391**	0,080%	0,973%	98,947%
Model 11	0,53065	3,140%	0,80049	84,266%	58,15%	0,02418	0,302%	0,200%	99,497%
Model 12	0,53782	3,181%	0,80726	84,773%	58,70%	0,02437	0,620%	0,058%	99,322%
Model 13	0,59990	3,526%	0,88223	92,417%	56,20%	0,02666	0,103%	0,008%	99,889%
Model 14	0,59690	3,508%	0,87548	91,847%	55,65%	0,02648	0,005%	0,108%	99,887%
Model 15	0,61761	3,653%	0,89547	94,176%	53,59%	0,02703	0,791%	0,087%	99,122%
Model 16	0,62652	3,706%	0,90412	94,962%	53,91%	0,02727	1,338%	0,235%	98,428%
Model 17	**0,52086**	**3,068%**	**0,78482**	**82,030%**	**60,00%**	**0,02373**	0,009%	0,414%	99,578%
Model 18	**0,52079**	**3,070%**	**0,78375**	**82,062%**	**59,67%**	**0,02371**	0,030%	0,668%	99,302%
Model 19	0,52847	3,123%	0,79446	83,286%	57,93%	0,02399	0,404%	0,083%	99,513%
Model 20	0,53531	3,162%	0,80139	83,832%	58,15%	0,02419	0,755%	0,007%	99,238%

Table 10: Performance statistics for predictive models with rolling estimation window

	MAE	MAPE	RMSE	Theil-U	MCPDC	Theil-I	Bias	Variance	Covariance
Model 1	0,66588	3,946%	0,94592	99,394%	50,54%	0,02851	1,751%	0,202%	98,048%
Model 2	0,57619	3,419%	0,84357	88,665%	54,13%	0,02544	1,536%	0,000%	98,464%
Model 3	0,66341	3,939%	0,93725	98,692%	50,87%	0,02825	2,105%	0,309%	97,586%
Model 4	0,57503	3,409%	0,83883	87,899%	54,13%	0,02529	1,775%	0,022%	98,203%
Model 5	0,60950	3,588%	0,88805	93,101%	56,74%	0,02685	0,013%	0,175%	99,812%
Model 6	0,61487	3,634%	0,88129	92,794%	57,93%	0,02667	0,119%	0,823%	99,058%
Model 7	0,62658	3,706%	0,90810	95,507%	53,48%	0,02741	0,660%	0,037%	99,303%
Model 8	0,63509	3,754%	0,91793	96,223%	52,50%	0,02769	1,357%	0,169%	98,475%
Model 9	**0,52793**	**3,126%**	**0,78792**	**83,098%**	60,33%	**0,02383**	0,000%	0,774%	99,225%
Model 10	0,53230	3,163%	0,78912	83,565%	**61,85%**	0,02388	0,089%	1,629%	98,282%
Model 11	0,53496	3,174%	0,80257	84,785%	59,24%	0,02424	0,394%	0,087%	99,519%
Model 12	0,54376	3,223%	0,81169	85,447%	58,80%	0,02450	0,876%	0,003%	99,122%
Model 13	0,60491	3,567%	0,87887	92,204%	56,85%	0,02656	0,061%	0,127%	99,812%
Model 14	0,60947	3,608%	0,87274	91,913%	58,26%	0,02640	0,033%	0,701%	99,266%
Model 15	0,62130	3,681%	0,89620	94,471%	54,13%	0,02705	0,687%	0,069%	99,244%
Model 16	0,63093	3,737%	0,90651	95,279%	54,35%	0,02734	1,446%	0,256%	98,299%
Model 17	**0,52543**	**3,108%**	**0,78080**	**81,922%**	**61,30%**	**0,02361**	0,013%	0,574%	99,413%
Model 18	**0,52970**	**3,144%**	**0,78131**	**82,276%**	**61,63%**	**0,02364**	0,040%	1,343%	98,617%
Model 19	0,53402	3,166%	0,79604	83,712%	58,26%	0,02404	0,512%	0,027%	99,462%
Model 20	0,54247	3,212%	0,80540	84,439%	57,93%	0,02431	1,047%	0,006%	98,947%

5. FINAL REMARKS

5.1 Key results

Through the analysis conducted in this work, we reach a number of important conclusions:

- Put-call ratio and implied volatility skew variables do have statistical significant predictive power with respect to future dynamics of VIX futures. Through univariate and multivariate regressions, we assessed the significance of the coefficients for both sub-sets of variables, and we obtained positive results in these terms.
- Predictive models, which include these variables, perform better than the benchmark model. We confront the performance of the benchmark model versus models including put-call ratio and implied volatility skew variables with respect to their accuracy in out-of-sample forecast. The results indicate how a predictive model, which does not include any of these variables, does underperform predictive models, which instead include them.
- There is an additional contribution to the forecasting accuracy when the combine effects of these variables is considered. Predictive models constructed using the two sub-samples of variables do perform better in the out-of-sample forecast exercise, showing better statistical indicators with respect to their performance.
- In the put-call ratio variables sample, the ones performing better are those computed using raw total daily traded volumes instead of smoothed volumes. This can be explained by the the fact that through the smoothing process we lost valuable information contained in the specific daily traded volumes.
- Among implied volatility skew variables, those performing better are the ones computed using moneyness levels of 90% and 110%. This may be related to the lower market liquidity for contracts with more extreme moneyness levels, which may impair the ability of new information to be quickly incorporated in those contracts.

5.2 Limitations

- One limitation of this work is the approach followed to compute the implied volatility skew variables. Constant levels of moneyness at 80%, 90%, 100%, 110% and 120% with associated implied volatilities have been used. The data have been derived through a linear interpolation process. Given the shape VIX options implied volatility surface, more accurate results may be obtained through a more sophisticated interpolation procedure, for example using a polynomial function instead of a linear one.
- Another limitation is that the analysis started from a model in levels and not in differences, thus limiting the scope of our analysis. This approach is justified by the presence of a cointregating relationship between VIX index and VIX futures, which makes us comfortable we are not dealing with spurious regressions. Nevertheless, we could have used an error correction model to define the base model, in order to fully capture the dynamics between VIX index and VIX futures and possibly improve the accuracy of the forecast.

5.3 Extensions

The analysis conducted in this work could be extended in the following way.

- The predictive power of implied volatility skew may be assessed with respect to VIX futures on longer maturity, i.e. 2nd or 3rd generic VIX future (ticker: VX2 and VX3). Specifically, the interpolation process could target a constant value of implied volatility at 60 or 90 days.
- The base model may be more accurately specified through a vector error correction model (VECM), given the cointegration and the bi-directional causality between VIX index and VIX futures.
- VIX weekly futures and VIX weekly options began trading at CBOE on July, 23rd 2015 and October, 8th 2015, respectively. The analysis we did in this work may be conducted using data derived from these new securities and investigate if put-call ratio and implied skew variables still retain forecasting power.

6. CONCLUSION

The existing literature dealing with the information content of option markets with respect to the underlying assets mainly focuses on one type of information at a time, either the put-call ratio or the implied volatility skew. We consider the combine effect of the two set of information in our analysis. Furthermore, we assess the information spillover from VIX options markets instead of equity options markets. VIX options began to trade in 2006 and the empirical literature concerning them is still far from being exhaustive. The contribution of this work is then clear: investigate the combined predictive power of put-call ratio and implied volatility skew of VIX options with respect to VIX futures. In our analysis, we first construct a number of independent variables:

- eight put-call ratio variables, both normal and smoothed, according to different maturity buckets given the fact that different kind of information may be revealed from the trading volumes of contracts having different expirations.
- nine implied volatility skew variables, considering both the skew within the same option contract type (i.e. spreads between out-of-the-money and at-the-money call options) and between call and put options (i.e. spreads between at-the-money call and at-the-money put options). We also differentiated the variables computing them with different levels of moneyness: 90%-110% for OTM and ITM versus 80%-120% for “deep” OTM and ITM.

As a second step, we conduct an in-sample analysis where we run a number of multivariate regressions, following different procedures, in order to identify the most significant variables. We employ these variables to build twenty different predictive models. The last part of the work focuses on the evaluation of the out-of-sample forecasting performance of twenty different models, through a wide variety of statistical indicators. The results indicate that both put-call ratio and implied volatility skew have predictive power with respect to VIX futures, and the forecasting accuracy increases when the two sets of information are considered together. Put-call ratios computed using raw daily trading volume perform better then those derived using smoothed volumes. Both the implied volatility skew within the same type of contract and the spread in volatilities between call and put options have forecasting power with respect to VIX futures.

7. REFERENCES

1. An, Ang, Bali and Cakici. (2014). “The Joint Cross Section of Stocks and Options”. *Journal of Finance*, 69(5), 2279.

2. Ang, A., R.J. Hodrick, Y. Xing, and X. Zhang. (2006). “The Cross Section of Volatility and Expected Returns”. *Journal of Finance*, 61(1), 259-299.

3. Arak, Marcelle, and Naranchimeg Mijid. (2006). “The VIX and VXN Volatility Measures: Fear Gauges or Forecasts?”. *Derivatives Use, Trading & Regulation*, 12(1),14-27.

4. Bandopadhyaya, Arindam and Anne Leah Jones. (2006). “Measuring Investor Sentiment in Equity Markets”. *Journal of Asset Management*, 7, 208-215.

5. Banerjee, Prithviraj, James Doran, and David Peterson. (2007). “Implied volatility and future portfolio returns”. *Journal of Banking & Finance*, 31, 3183-3199.

6. Bardelli Giulia. (2014). “The information content of VIX options: combining the put-call ratio and the implied volatility skew”. *Master thesis, Bocconi University*.

7. Becker, Ralf, Adam E. Clements and Andrew McClelland. (2009). "The Jump Component of S&P 500 Volatility and the VIX Index". *Journal of Banking & Finance*, 33(6), 1033-1038.

8. Becker, R., Clements, A. E., and White, S. I. (2007). “Does implied volatility provide any information beyond that captured in model-based volatility forecasts?”. *Journal of Banking and Finance*, 31, 2535-2549.

9. Bedendo, M., and Hodges, S.D. (2009). “The dynamics of the volatility skew: A Kalman filter approach”. *Journal of Banking and Finance*, 33, 1156-1165.

10. Blair, B. J., Poon, S., and Taylor, S.J. (2001). “Forecasting S&P 100 volatility: The incremental information content of implied volatilities and high-frequency index returns”. *Journal of Econometrics*, 105, 5-26.

11. Bollen, N., and R. Whaley. (2004). “Does Net Buying Pressure Affect the Shape of Implied Volatility Functions?”. *Journal of Finance*, 59, 711-753.

12. Brenner, M., and D. Galai. (1996). "Options on Volatility". *Option Embedded Bonds*, 13, 273-286.

13. Canina, L., and Figlewski, S. (1993). “The information content of implied volatility”. *Review of Financial Studies*, 6, 659-681.

14. Chakravarty, S., Gulen, H., and Mayhew, S. (2004). “Informed trading in stock and option markets”. *Journal of Finance*, 59, 1235-1257.

15. Chan, K., Chung, Y.-P., and Fong, W.-M. (2002). “The informational role of stock and option volume”. *Review of Financial Studies*, 15, 1049-1075.

16. Chang, C.-C., Hsieh, P.-F., and Lai, H.-N. (2009). “Do informed option investors predict stock returns? Evidence from the Taiwan stock exchange”. *Journal of Banking and Finance*, 33, 757-764.

17. Christensen, B.J., and N.R. Prabhala. (1998). “The Relation between Implied and Realized Volatility”. *Journal of Financial Economics*, 50(2), 125-150.

18. Chung, S.-L., Tsai, W.-C., Wang, Y.-H. and Weng, P.-S. (2011). “The Information Content of the S&P 500 index and VIX Options on the Dynamics of the S&P 500 index”. *Journal of Futures Markets.*

19. Cremers, M., and Weinbaum, D. (2010). “Deviations from put-call parity and stock return predictability”. *Journal of Financial and Quantitative Analysis*, 45, 335-367.

20. Das, S., and Sundaram, R. (1999). “Of smiles and smirks: A term structure perspective”. *Journal of Financial and Quantitative Analysis*, 34(1), 60-72.

21. Dennis, Patrick and Stewart Mayhew. (2002). “Risk-Neutral Skewness: Evidence from Stock Options”. *Journal of Financial & Quantitative Analysis*, 37(3), 471-493.

22. Derman, Emanuel, and Iraj Kani. (1994). “Riding on the smile”. *Risk*, 7, 32-39.

23. Detemple J. and C. Osakwe. (2000). "The Valuation of Volatility Options". *European Finance Review.*

24. Diavatopoulos, C., J. Doran, and D. Peterson. (2008). “The Information Content in Implied Idiosyncratic Volatility and the Cross-Section of Stock Returns: Evidence from the Option Markets”. *Journal of Futures Markets*, 28(11), 1013-1039.

25. Doran, J.S., Peterson, D.R., and Tarrant, B.C. (2007). “Is there information in the volatility skew?”. *Journal of Futures Markets*, 27, 921-959.

26. Easley, D., O’Hara, M., and Srinivas, P. (1998). “Option volume and stock prices: Evidence on where informed traders trade”. *Journal of Finance*, 53, 431-466.

27. Giot, P. (2005). “Relationships between implied volatility indexes and stock index returns”. *Journal of Portfolio Management*, 26, 12-17.

28. Grünbichler, A., and Longstaff, F. A. (1996). “Valuing futures and options on volatility”. *Journal of Banking and Finance*, 20, 985-1001.

29. Johnson, T.L. and So, E.C. (2012). “The Option to Stock Volume Ratio and Future Returns”. *Journal of Financial Economics*, 106(2), 262-286.

30. Konstantinidi, E. and Skiadopoulos, G. (2011). “Are VIX futures prices predictable? An empirical investigation”. *International Journal of Forecasting*, 2011, 27(2), 543-560.

31. Kozyraa, James, and Camillo Lentoa. (2011). “Using VIX Data to Enhance Technical Trading Signals”. *Applied Economics Letters*, 18(14), 1367-1370.

32. Lin, Y., and Chang, C. (2009). “VIX Option pricing”. *Journal of Futures Market*, 29, 523-543.

33. Moran, and Matthew T. (2004). "Review of the VIX Index and VIX Futures”. *Journal of Indexes*, 16-19.

34. Ni, S.X., Pan, J., and Poteshman, A.M. (2008). “Volatility information trading in the option market”. *Journal of Finance*, 63, 1059-1091.

35. Nossman, Marcus and Anders Wilhelmsson. (2009). “Is the VIX Futures Market Able to Predict the VIX Index? A Test of the Expectation Hypothesis”. *The Journal of Alternative Investments*, 12(2), 54-67.

36. Pan, J., and Poteshman, A.M. (2006). “The information in option volume for future stock price”. *Review of Financial Studies*, 19, 871-908.

37. Sepp, A. (2008). “VIX Option pricing in a jump-diffusion model”. *Risk*, April, 84-89.

38. Sepp, A. (2008). “Pricing options on realized variance in a Heston model with jumps in returns and volatility”. *Journal of Computational Finance*, 11, 33-70.

39. Shu, Jinghong, and Jin E. Zhang. (2012). “Causality in the VIX Futures Market”. *Journal of Futures Markets*, 32, 24-46.

40. Wang, Z., and Daigler, R. T. (2010). “The performance of VIX option pricing models: Empirical evidence beyond simulation”. *Journal of Futures Markets*, 31, 251-281.

41. Whaley, R. E. (1993). “Derivatives on market volatility: Hedging tools long overdue”. *Journal of Derivatives*, 1, 71-84.

42. Whaley, R. E. (2000). “The investor fear gauge”. *Journal of Portfolio Management*, 26, 12-17.

43. Zhang, J. E., and Zhu, Y. (2006). “VIX futures”. *Journal of Futures Markets*, 26, 521-531.

8. APPENDIX

Panel 1: Augmented Dickey-Fuller test for VIX Index

Null Hypothesis: VIXSPOT has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.674670	0.0242
Test critical values:	1% level	-3.962264	
	5% level	-3.411874	
	10% level	-3.127832	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(VIXSPOT)
Method: Least Squares
Date: 05/02/16 Time: 09:14
Sample (adjusted): 1/10/2007 8/31/2015
Included observations: 2176 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VIXSPOT(-1)	-0.017366	0.004726	-3.674670	0.0002
D(VIXSPOT(-1))	-0.141682	0.021491	-6.592642	0.0000
D(VIXSPOT(-2))	-0.097534	0.021649	-4.505156	0.0000
D(VIXSPOT(-3))	-0.058217	0.021645	-2.689634	0.0072
D(VIXSPOT(-4))	-0.094061	0.021451	-4.384866	0.0000
C	0.514659	0.160751	3.201579	0.0014
@TREND("1/03/2007")	-0.000122	7.53E-05	-1.614197	0.1066

R-squared	0.043370	Mean dependent var	0.007592
Adjusted R-squared	0.040724	S.D. dependent var	2.038502
S.E. of regression	1.996562	Akaike info criterion	4.223942
Sum squared resid	8646.199	Schwarz criterion	4.242231
Log likelihood	-4588.649	Hannan-Quinn criter.	4.230629
F-statistic	16.38920	Durbin-Watson stat	2.004373
Prob(F-statistic)	0.000000		

Panel 2: Augmented Dickey-Fuller test for 1st Generic VIX Future

Null Hypothesis: _1FUTURE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.510797	0.0384
Test critical values:	1% level	-3.962260	
	5% level	-3.411872	
	10% level	-3.127831	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(_1FUTURE)
Method: Least Squares
Date: 05/02/16 Time: 09:17
Sample (adjusted): 1/08/2007 8/31/2015
Included observations: 2178 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
_1FUTURE(-1)	-0.012444	0.003544	-3.510797	0.0005
D(_1FUTURE(-1))	-0.068463	0.021412	-3.197440	0.0014
D(_1FUTURE(-2))	-0.073058	0.021394	-3.414919	0.0006
C	0.370459	0.116904	3.168915	0.0016
@TREND("1/03/2007")	-8.41E-05	5.14E-05	-1.634921	0.1022

R-squared	0.016528	Mean dependent var	0.006449
Adjusted R-squared	0.014718	S.D. dependent var	1.377018
S.E. of regression	1.366847	Akaike info criterion	3.465183
Sum squared resid	4059.752	Schwarz criterion	3.478237
Log likelihood	-3768.585	Hannan-Quinn criter.	3.469956
F-statistic	9.129657	Durbin-Watson stat	2.002941
Prob(F-statistic)	0.000000		

Panel 3: Augmented Dickey-Fuller test for Delta VIX Index

Null Hypothesis: D(VIXSPOT) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-28.61474	0.0000
Test critical values:	1% level	-3.962264	
	5% level	-3.411874	
	10% level	-3.127832	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(VIXSPOT,2)
Method: Least Squares
Date: 05/02/16 Time: 09:15
Sample (adjusted): 1/10/2007 8/31/2015
Included observations: 2176 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(VIXSPOT(-1))	-1.426073	0.049837	-28.61474	0.0000
D(VIXSPOT(-1),2)	0.273892	0.041954	6.528448	0.0000
D(VIXSPOT(-2),2)	0.167167	0.032611	5.126116	0.0000
D(VIXSPOT(-3),2)	0.100930	0.021431	4.709506	0.0000
C	0.015288	0.086116	0.177528	0.8591
@TREND("1/03/2007")	-3.98E-06	6.83E-05	-0.058188	0.9536

R-squared	0.574269	Mean dependent var	0.001135
Adjusted R-squared	0.573288	S.D. dependent var	3.065230
S.E. of regression	2.002306	Akaike info criterion	4.229230
Sum squared resid	8700.026	Schwarz criterion	4.244906
Log likelihood	-4595.402	Hannan-Quinn criter.	4.234961
F-statistic	585.4235	Durbin-Watson stat	2.006049
Prob(F-statistic)	0.000000		

Panel 4: Augmented Dickey-Fuller test for Delta 1st Generic VIX Future

Null Hypothesis: D(_1FUTURE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.86641	0.0000
Test critical values:	1% level	-3.962260	
	5% level	-3.411872	
	10% level	-3.127831	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(_1FUTURE,2)
Method: Least Squares
Date: 05/02/16 Time: 09:18
Sample (adjusted): 1/08/2007 8/31/2015
Included observations: 2178 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(_1FUTURE(-1))	-1.153373	0.031285	-36.86641	0.0000
D(_1FUTURE(-1),2)	0.078579	0.021392	3.673380	0.0002
C	0.015481	0.058832	0.263133	0.7925
@TREND("1/03/2007")	-7.49E-06	4.67E-05	-0.160410	0.8726

R-squared	0.537301	Mean dependent var	0.000794
Adjusted R-squared	0.536662	S.D. dependent var	2.013258
S.E. of regression	1.370403	Akaike info criterion	3.469921
Sum squared resid	4082.780	Schwarz criterion	3.480364
Log likelihood	-3774.744	Hannan-Quinn criter.	3.473739
F-statistic	841.5061	Durbin-Watson stat	2.004159
Prob(F-statistic)	0.000000		

Panel 5: Johansen cointegration test for VIX index and VIX futures

Date: 05/10/16 Time: 16:33
Sample (adjusted): 1/10/2007 8/31/2015
Included observations: 2176 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: _1FUTURE VIXSPOT
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.055373	138.5148	25.87211	0.0000
At most 1 *	0.006669	14.55960	12.51798	0.0225

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.055373	123.9552	19.38704	0.0001
At most 1 *	0.006669	14.55960	12.51798	0.0225

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

_1FUTURE	VIXSPOT	@TREND(1/04/07)
-0.680594	0.625676	-2.34E-05
-0.108845	-0.012034	-0.000767

Unrestricted Adjustment Coefficients (alpha):

D(_1FUTURE)	0.169678	0.094416
D(VIXSPOT)	-0.018655	0.161907

1 Cointegrating Equation(s): Log likelihood -7026.204

Normalized cointegrating coefficients (standard error in parentheses)

_1FUTURE	VIXSPOT	@TREND(1/04/07)
1.000000	-0.919309	3.43E-05
	(0.01443)	(0.00023)

Adjustment coefficients (standard error in parentheses)

D(_1FUTURE)	-0.115482
	(0.01977)
D(VIXSPOT)	0.012696
	(0.02902)

Panel 6: Base Model with VIX Index Lagged and VIX Future Lagged

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 10:22
Sample (adjusted): 1/04/2007 8/31/2015
Included observations: 2180 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.440710	0.083257	5.293345	0.0000
_1FUTURE(-1)	0.902875	0.016724	53.98608	0.0000
VIXSPOT(-1)	0.078810	0.015102	5.218483	0.0000

R-squared	0.977887	Mean dependent var	21.80986
Adjusted R-squared	0.977867	S.D. dependent var	9.171855
S.E. of regression	1.364508	Akaike info criterion	3.460841
Sum squared resid	4053.320	Schwarz criterion	3.468667
Log likelihood	-3769.316	Hannan-Quinn criter.	3.463702
F-statistic	48136.89	Durbin-Watson stat	2.168751
Prob(F-statistic)	0.000000		

Panel 7: Correlogram of Residuals from Base Model up to 10 Lags

Date: 05/02/16 Time: 10:24
Sample: 1/03/2007 8/31/2015
Included observations: 2180
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.085	-0.085	15.706	0.000
		2	-0.078	-0.086	28.962	0.000
		3	-0.023	-0.038	30.102	0.000
		4	0.018	0.006	30.817	0.000
		5	-0.071	-0.075	41.942	0.000
		6	0.033	0.021	44.278	0.000
		7	-0.030	-0.038	46.295	0.000
		8	-0.030	-0.037	48.292	0.000
		9	-0.037	-0.047	51.286	0.000
		10	0.057	0.036	58.320	0.000

*Probabilities may not be valid for this equation specification.

Panel 8: LM Serial Correlation Test for Residuals from Base Model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	7.087545	Prob. F(10,2167)	0.0000
Obs*R-squared	69.04248	Prob. Chi-Square(10)	0.0000

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/02/16 Time: 10:24
Sample: 1/04/2007 8/31/2015
Included observations: 2180
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.191584	0.088672	-2.160586	0.0308
_1FUTURE(-1)	-0.000469	0.016581	-0.028265	0.9775
VIXSPOT(-1)	0.009419	0.015044	0.626084	0.5313
RESID(-1)	-0.109093	0.022160	-4.922883	0.0000
RESID(-2)	-0.108381	0.022102	-4.903703	0.0000
RESID(-3)	-0.057294	0.022136	-2.588245	0.0097
RESID(-4)	-0.018149	0.022107	-0.820957	0.4118
RESID(-5)	-0.088138	0.022100	-3.988133	0.0001
RESID(-6)	-0.001115	0.022125	-0.050409	0.9598
RESID(-7)	-0.057152	0.022136	-2.581820	0.0099
RESID(-8)	-0.051043	0.022139	-2.305566	0.0212
RESID(-9)	-0.055317	0.022003	-2.514109	0.0120
RESID(-10)	0.025117	0.021909	1.146433	0.2517

R-squared	0.031671	Mean dependent var	1.99E-15
Adjusted R-squared	0.026309	S.D. dependent var	1.363882
S.E. of regression	1.345822	Akaike info criterion	3.437832
Sum squared resid	3924.948	Schwarz criterion	3.471746
Log likelihood	-3734.237	Hannan-Quinn criter.	3.450230
F-statistic	5.906287	Durbin-Watson stat	1.996904
Prob(F-statistic)	0.000000		

Panel 9: Heteroskedasticity Test for Residuals from Base Model

Heteroskedasticity Test: White

F-statistic	123.8172	Prob. F(5,2174)	0.0000
Obs*R-squared	483.1957	Prob. Chi-Square(5)	0.0000
Scaled explained SS	2466.604	Prob. Chi-Square(5)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/02/16 Time: 10:25
Sample: 1/04/2007 8/31/2015
Included observations: 2180

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.932946	0.799803	1.166469	0.2436
_1FUTURE(-1)^2	-0.031792	0.014584	-2.179904	0.0294
_1FUTURE(-1)*VIXSPOT(-1)	0.059513	0.023349	2.548868	0.0109
_1FUTURE(-1)	-0.261924	0.205743	-1.273066	0.2031
VIXSPOT(-1)^2	-0.023091	0.009483	-2.434993	0.0150
VIXSPOT(-1)	0.195849	0.173276	1.130273	0.2585

R-squared	0.221649	Mean dependent var	1.859321
Adjusted R-squared	0.219859	S.D. dependent var	5.950524
S.E. of regression	5.255834	Akaike info criterion	6.159303
Sum squared resid	60054.13	Schwarz criterion	6.174956
Log likelihood	-6707.640	Hannan-Quinn criter.	6.165025
F-statistic	123.8172	Durbin-Watson stat	1.867981
Prob(F-statistic)	0.000000		

Panel 10: Base Model re-estimated with HAC Covariance Method

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 10:27
Sample (adjusted): 1/04/2007 8/31/2015
Included observations: 2180 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.440710	0.100923	4.366783	0.0000
_1FUTURE(-1)	0.902875	0.028826	31.32145	0.0000
VIXSPOT(-1)	0.078810	0.027344	2.882184	0.0040

R-squared	0.977887	Mean dependent var	21.80986
Adjusted R-squared	0.977867	S.D. dependent var	9.171855
S.E. of regression	1.364508	Akaike info criterion	3.460841
Sum squared resid	4053.320	Schwarz criterion	3.468667
Log likelihood	-3769.316	Hannan-Quinn criter.	3.463702
F-statistic	48136.89	Durbin-Watson stat	2.168751
Prob(F-statistic)	0.000000	Wald F-statistic	21905.36
Prob(Wald F-statistic)	0.000000		

Panel 11: Model with Put-Call Ratios Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 10:45
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 1924 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.470353	0.135240	3.477925	0.0005
_1FUTURE(-1)	0.938344	0.034287	27.36757	0.0000
VIXSPOT(-1)	0.052579	0.031868	1.649919	0.0991
PCR130	-0.168627	0.037353	-4.514375	0.0000
PCR1545	0.003277	0.058707	0.055825	0.9555
PCR160	-0.082732	0.127319	-0.649802	0.5159
PCRALL	-0.241496	0.114929	-2.101257	0.0357
TOTALVOLUME	2.29E-07	1.38E-07	1.653614	0.0984

R-squared	0.978912	Mean dependent var	21.94410
Adjusted R-squared	0.978835	S.D. dependent var	9.271782
S.E. of regression	1.348874	Akaike info criterion	3.440567
Sum squared resid	3486.088	Schwarz criterion	3.463694
Log likelihood	-3301.825	Hannan-Quinn criter.	3.449076
F-statistic	12705.99	Durbin-Watson stat	2.226880
Prob(F-statistic)	0.000000	Wald F-statistic	6242.867
Prob(Wald F-statistic)	0.000000		

Panel 12: Model with Smoothed Put-Call Ratios Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 10:43
Sample (adjusted): 1/09/2007 8/31/2015
Included observations: 2162 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.407118	0.118803	3.426838	0.0006
_1FUTURE(-1)	0.916518	0.032589	28.12365	0.0000
VIXSPOT(-1)	0.069326	0.029942	2.315349	0.0207
PCR130SM	0.061251	0.045275	1.352874	0.1762
PCR1545SM	0.111843	0.131919	0.847817	0.3966
PCR160SM	-0.304220	0.229615	-1.324911	0.1853
PCRALLSM	-0.097258	0.253253	-0.384034	0.7010
TOTALVOLUME	1.92E-07	1.40E-07	1.371584	0.1703

R-squared	0.977864	Mean dependent var	21.87086
Adjusted R-squared	0.977792	S.D. dependent var	9.183420
S.E. of regression	1.368545	Akaike info criterion	3.469067
Sum squared resid	4034.259	Schwarz criterion	3.490080
Log likelihood	-3742.061	Hannan-Quinn criter.	3.476752
F-statistic	13593.33	Durbin-Watson stat	2.183918
Prob(F-statistic)	0.000000	Wald F-statistic	7128.131
Prob(Wald F-statistic)	0.000000		

Panel 13: Model with Implied Volatility Skew Variables (except CAPA)

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:31
Sample (adjusted): 1/05/2007 8/28/2015
Included observations: 2166 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.510112	0.237390	6.361315	0.0000
_1FUTURE(-1)	0.882536	0.030876	28.58364	0.0000
VIXSPOT(-1)	0.079752	0.027865	2.862067	0.0042
AMB	-2.606554	1.682900	-1.548846	0.1216
COMA	4.036683	2.437177	1.656295	0.0978
PAMO	2.417661	1.799176	1.343760	0.1792
COPA	-8.587569	1.509189	-5.690188	0.0000

R-squared	0.978522	Mean dependent var	21.87047
Adjusted R-squared	0.978463	S.D. dependent var	9.164939
S.E. of regression	1.345009	Akaike info criterion	3.433905
Sum squared resid	3905.737	Schwarz criterion	3.452263
Log likelihood	-3711.919	Hannan-Quinn criter.	3.440619
F-statistic	16394.05	Durbin-Watson stat	2.150576
Prob(F-statistic)	0.000000	Wald F-statistic	8054.188
Prob(Wald F-statistic)	0.000000		

Panel 14: Model with Implied Volatility Skew Variables (except COPA)

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:31
Sample (adjusted): 1/05/2007 8/28/2015
Included observations: 2166 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.510112	0.237390	6.361315	0.0000
_1FUTURE(-1)	0.882536	0.030876	28.58364	0.0000
VIXSPOT(-1)	0.079752	0.027865	2.862067	0.0042
AMB	-2.606554	1.682900	-1.548846	0.1216
COMA	-4.550886	2.255893	-2.017333	0.0438
PAMO	2.417661	1.799176	1.343760	0.1792
CAPA	-8.587569	1.509189	-5.690188	0.0000

R-squared	0.978522	Mean dependent var	21.87047
Adjusted R-squared	0.978463	S.D. dependent var	9.164939
S.E. of regression	1.345009	Akaike info criterion	3.433905
Sum squared resid	3905.737	Schwarz criterion	3.452263
Log likelihood	-3711.919	Hannan-Quinn criter.	3.440619
F-statistic	16394.05	Durbin-Watson stat	2.150576
Prob(F-statistic)	0.000000	Wald F-statistic	8054.188
Prob(Wald F-statistic)	0.000000		

Panel 15: Model with Deep Implied Volatility Skew Variables (except CAPA)

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:30
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2167 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.656892	0.240334	6.894130	0.0000
_1FUTURE(-1)	0.888742	0.031072	28.60225	0.0000
VIXSPOT(-1)	0.072215	0.028173	2.563231	0.0104
DAMB	-0.650427	0.605524	-1.074157	0.2829
DCOMA	4.270844	1.911218	2.234620	0.0255
DPAMO	1.283254	0.650433	1.972923	0.0486
DCOPA	-8.976016	1.513802	-5.929450	0.0000

R-squared	0.978684	Mean dependent var	21.87257
Adjusted R-squared	0.978625	S.D. dependent var	9.163345
S.E. of regression	1.339707	Akaike info criterion	3.426003
Sum squared resid	3876.798	Schwarz criterion	3.444355
Log likelihood	-3705.075	Hannan-Quinn criter.	3.432714
F-statistic	16528.69	Durbin-Watson stat	2.139357
Prob(F-statistic)	0.000000	Wald F-statistic	7672.249
Prob(Wald F-statistic)	0.000000		

Panel 16: Model with Deep Implied Volatility Skew Variables (except DCOPA)

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:30
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2167 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.656892	0.240334	6.894130	0.0000
_1FUTURE(-1)	0.888742	0.031072	28.60225	0.0000
VIXSPOT(-1)	0.072215	0.028173	2.563231	0.0104
DAMB	-0.650427	0.605524	-1.074157	0.2829
DCOMA	-4.705171	1.074915	-4.377249	0.0000
DPAMO	1.283254	0.650433	1.972923	0.0486
CAPA	-8.976016	1.513802	-5.929450	0.0000

R-squared	0.978684	Mean dependent var	21.87257
Adjusted R-squared	0.978625	S.D. dependent var	9.163345
S.E. of regression	1.339707	Akaike info criterion	3.426003
Sum squared resid	3876.798	Schwarz criterion	3.444355
Log likelihood	-3705.075	Hannan-Quinn criter.	3.432714
F-statistic	16528.69	Durbin-Watson stat	2.139357
Prob(F-statistic)	0.000000	Wald F-statistic	7672.249
Prob(Wald F-statistic)	0.000000		

Panel 17: Model with Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:23
Sample (adjusted): 1/05/2007 8/28/2015
Included observations: 1915 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.629574	0.254057	6.414198	0.0000
_1FUTURE(-1)	0.909986	0.034737	26.19660	0.0000
VIXSPOT(-1)	0.059315	0.031199	1.901208	0.0574
PCR130	-0.152585	0.036911	-4.133890	0.0000
PCR1545	0.004865	0.055262	0.088040	0.9299
PCR160	-0.149302	0.118230	-1.262818	0.2068
PCRALL	-0.180043	0.106055	-1.697632	0.0897
AMB	-3.231283	1.759432	-1.836549	0.0664
COMA	-2.440846	2.426770	-1.005800	0.3146
PAMO	1.823400	1.718226	1.061211	0.2887
CAPA	-9.463688	1.608041	-5.885228	0.0000

R-squared	0.979599	Mean dependent var	21.98611
Adjusted R-squared	0.979492	S.D. dependent var	9.267489
S.E. of regression	1.327165	Akaike info criterion	3.409694
Sum squared resid	3353.640	Schwarz criterion	3.441617
Log likelihood	-3253.782	Hannan-Quinn criter.	3.421441
F-statistic	9142.498	Durbin-Watson stat	2.204680
Prob(F-statistic)	0.000000	Wald F-statistic	5034.701
Prob(Wald F-statistic)	0.000000		

Panel 18: Model with Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 11:34
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 1916 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.688800	0.255356	6.613516	0.0000
_1FUTURE(-1)	0.911651	0.034957	26.07950	0.0000
VIXSPOT(-1)	0.057134	0.031527	1.812185	0.0701
PCR130	-0.144106	0.036991	-3.895754	0.0001
PCR1545	0.006029	0.055456	0.108725	0.9134
PCR160	-0.143334	0.117806	-1.216694	0.2239
PCRALL	-0.186367	0.106084	-1.756782	0.0791
DAMB	-1.447774	0.669761	-2.161626	0.0308
DCOMA	-2.351332	1.130010	-2.080806	0.0376
DPAMO	1.111079	0.683642	1.625236	0.1043
CAPA	-9.849637	1.639519	-6.007639	0.0000

R-squared	0.979627	Mean dependent var	21.98843
Adjusted R-squared	0.979520	S.D. dependent var	9.265624
S.E. of regression	1.325988	Akaike info criterion	3.407917
Sum squared resid	3349.454	Schwarz criterion	3.439826
Log likelihood	-3253.784	Hannan-Quinn criter.	3.419659
F-statistic	9160.091	Durbin-Watson stat	2.193219
Prob(F-statistic)	0.000000	Wald F-statistic	4780.138
Prob(Wald F-statistic)	0.000000		

Panel 19: Model with Smoothed Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:26
Sample (adjusted): 1/09/2007 8/28/2015
Included observations: 2151 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.589142	0.236716	6.713294	0.0000
_1FUTURE(-1)	0.889797	0.033204	26.79769	0.0000
VIXSPOT(-1)	0.074427	0.029390	2.532397	0.0114
PCR130SM	0.072474	0.042674	1.698316	0.0896
PCR1545SM	0.059845	0.138055	0.433488	0.6647
PCR160SM	-0.309773	0.256089	-1.209628	0.2266
PCRALLSM	-0.052010	0.275084	-0.189069	0.8501
AMB	-2.663842	1.701556	-1.565533	0.1176
COMA	-4.262236	2.298861	-1.854064	0.0639
PAMO	2.185282	1.798994	1.214724	0.2246
CAPA	-8.759251	1.542538	-5.678467	0.0000

R-squared	0.978526	Mean dependent var	21.91816
Adjusted R-squared	0.978426	S.D. dependent var	9.177609
S.E. of regression	1.348027	Akaike info criterion	3.440261
Sum squared resid	3888.756	Schwarz criterion	3.469276
Log likelihood	-3689.001	Hannan-Quinn criter.	3.450876
F-statistic	9751.534	Durbin-Watson stat	2.165716
Prob(F-statistic)	0.000000	Wald F-statistic	5475.441
Prob(Wald F-statistic)	0.000000		

Panel 20: Model with Smoothed Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:25
Sample (adjusted): 1/09/2007 8/31/2015
Included observations: 2152 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.698739	0.241641	7.030022	0.0000
_1FUTURE(-1)	0.893287	0.033192	26.91291	0.0000
VIXSPOT(-1)	0.069338	0.029528	2.348253	0.0190
PCR130SM	0.078118	0.040878	1.910993	0.0561
PCR1545SM	0.047703	0.139376	0.342263	0.7322
PCR160SM	-0.204474	0.244743	-0.835463	0.4036
PCRALLSM	-0.085442	0.266882	-0.320149	0.7489
DAMB	-0.729855	0.609477	-1.197511	0.2312
DCOMA	-4.521757	1.095651	-4.127007	0.0000
DPAMO	1.270137	0.649003	1.957058	0.0505
CAPA	-9.146474	1.546981	-5.912469	0.0000

R-squared	0.978668	Mean dependent var	21.92025
Adjusted R-squared	0.978569	S.D. dependent var	9.175989
S.E. of regression	1.343312	Akaike info criterion	3.433252
Sum squared resid	3863.407	Schwarz criterion	3.462255
Log likelihood	-3683.179	Hannan-Quinn criter.	3.443862
F-statistic	9822.634	Durbin-Watson stat	2.155070
Prob(F-statistic)	0.000000	Wald F-statistic	5272.333
Prob(Wald F-statistic)	0.000000		

Panel 21: Final Model with Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 14:47
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2018 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.508635	0.223684	6.744479	0.0000
_1FUTURE(-1)	0.911624	0.032882	27.72376	0.0000
VIXSPOT(-1)	0.060412	0.029938	2.017905	0.0437
PCR130	-0.180524	0.033831	-5.336018	0.0000
PCRALL	-0.295545	0.076665	-3.855023	0.0001
COMA	-6.537230	1.117474	-5.850007	0.0000
CAPA	-9.511689	1.567152	-6.069410	0.0000

R-squared	0.979987	Mean dependent var	21.96038
Adjusted R-squared	0.979927	S.D. dependent var	9.275581
S.E. of regression	1.314152	Akaike info criterion	3.387723
Sum squared resid	3472.988	Schwarz criterion	3.407182
Log likelihood	-3411.212	Hannan-Quinn criter.	3.394865
F-statistic	16412.17	Durbin-Watson stat	2.188608
Prob(F-statistic)	0.000000	Wald F-statistic	7857.423
Prob(Wald F-statistic)	0.000000		

Panel 22: Final Model with Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 13:41
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2018 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.631288	0.240122	6.793587	0.0000
_1FUTURE(-1)	0.912582	0.032733	27.87934	0.0000
VIXSPOT(-1)	0.057588	0.029867	1.928135	0.0540
PCR130	-0.171570	0.033425	-5.133008	0.0000
PCRALL	-0.291559	0.076501	-3.811191	0.0001
DCOMA	-4.040235	0.682905	-5.916243	0.0000
CAPA	-9.320941	1.558944	-5.979009	0.0000

R-squared	0.980042	Mean dependent var	21.96038
Adjusted R-squared	0.979983	S.D. dependent var	9.275581
S.E. of regression	1.312331	Akaike info criterion	3.384949
Sum squared resid	3463.367	Schwarz criterion	3.404408
Log likelihood	-3408.414	Hannan-Quinn criter.	3.392091
F-statistic	16458.69	Durbin-Watson stat	2.179600
Prob(F-statistic)	0.000000	Wald F-statistic	7809.075
Prob(Wald F-statistic)	0.000000		

Panel 23: Final Model with Smoothed Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 14:52
Sample (adjusted): 1/09/2007 8/31/2015
Included observations: 2165 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.526844	0.215883	7.072553	0.0000
_1FUTURE(-1)	0.892850	0.031654	28.20625	0.0000
VIXSPOT(-1)	0.072531	0.028728	2.524775	0.0116
PCR160SM	-0.212612	0.092669	-2.294322	0.0219
COMA	-7.088997	1.114923	-6.358286	0.0000
CAPA	-8.861742	1.515403	-5.847781	0.0000

R-squared	0.978506	Mean dependent var	21.88140
Adjusted R-squared	0.978457	S.D. dependent var	9.162968
S.E. of regression	1.344910	Akaike info criterion	3.433299
Sum squared resid	3905.163	Schwarz criterion	3.449041
Log likelihood	-3710.546	Hannan-Quinn criter.	3.439056
F-statistic	19657.88	Durbin-Watson stat	2.152074
Prob(F-statistic)	0.000000	Wald F-statistic	9669.043
Prob(Wald F-statistic)	0.000000		

Panel 24: Final Model with Smoothed Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Least Squares
Date: 05/02/16 Time: 14:49
Sample (adjusted): 1/09/2007 8/31/2015
Included observations: 2165 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.744539	0.234768	7.430915	0.0000
_1FUTURE(-1)	0.891540	0.031546	28.26176	0.0000
VIXSPOT(-1)	0.069913	0.028588	2.445505	0.0145
PCR160SM	-0.163327	0.094675	-1.725129	0.0846
DCOMA	-4.754654	0.682946	-6.961978	0.0000
CAPA	-8.817605	1.497441	-5.888448	0.0000

R-squared	0.978656	Mean dependent var	21.88140
Adjusted R-squared	0.978606	S.D. dependent var	9.162968
S.E. of regression	1.340225	Akaike info criterion	3.426320
Sum squared resid	3878.004	Schwarz criterion	3.442062
Log likelihood	-3702.991	Hannan-Quinn criter.	3.432077
F-statistic	19798.58	Durbin-Watson stat	2.142373
Prob(F-statistic)	0.000000	Wald F-statistic	9476.789
Prob(Wald F-statistic)	0.000000		

Panel 25: Stepwise Model with Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:03
Sample (adjusted): 1/05/2007 8/28/2015
Included observations: 2017 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Stepwise forwards
Stopping criterion: p-value forwards/backwards = 0.1/0.1
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.967986	0.015769	61.38566	0.0000
VIXSPOT(-1)	0.036432	0.014922	2.441426	0.0147
CAPA	-7.563171	1.222685	-6.185705	0.0000
PCRALL	-0.279241	0.083536	-3.342753	0.0008
PAMO	1.533005	0.461245	3.323625	0.0009
PCR130	-0.156747	0.044367	-3.532983	0.0004

R-squared	0.979345	Mean dependent var	21.95816
Adjusted R-squared	0.979294	S.D. dependent var	9.277348
S.E. of regression	1.334978	Akaike info criterion	3.418678
Sum squared resid	3583.938	Schwarz criterion	3.435364
Log likelihood	-3441.736	Hannan-Quinn criter.	3.424802
Durbin-Watson stat	2.198853		

Selection Summary

Added CAPA
Added PCR160
Added PAMO
Added PCR130
Added PCRALL
Removed PCR160

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 26: Stepwise Model with Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:02
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2018 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Stepwise forwards
Stopping criterion: p-value forwards/backwards = 0.1/0.1
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.968201	0.015568	62.19081	0.0000
VIXSPOT(-1)	0.036167	0.014771	2.448483	0.0144
CAPA	-7.589794	1.220811	-6.217010	0.0000
PCRALL	-0.279947	0.083472	-3.353791	0.0008
DPAMO	0.837329	0.231985	3.609411	0.0003
PCR130	-0.157514	0.044337	-3.552616	0.0004

R-squared	0.979348	Mean dependent var	21.96038
Adjusted R-squared	0.979296	S.D. dependent var	9.275581
S.E. of regression	1.334646	Akaike info criterion	3.418178
Sum squared resid	3583.935	Schwarz criterion	3.434857
Log likelihood	-3442.941	Hannan-Quinn criter.	3.424299
Durbin-Watson stat	2.197076		

Selection Summary

Added CAPA
Added PCR160
Added DPAMO
Added PCR130
Added PCRALL
Removed PCR160

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 27: Stepwise Model with Smoothed Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 13:58
Sample (adjusted): 1/05/2007 8/28/2015
Included observations: 2166 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Stepwise forwards
Stopping criterion: p-value forwards/backwards = 0.1/0.1
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.943671	0.015465	61.02151	0.0000
VIXSPOT(-1)	0.052416	0.014818	3.537236	0.0004
CAPA	-4.763398	1.599078	-2.978840	0.0029
PAMO	3.004064	1.118284	2.686316	0.0073
COPA	-2.454313	1.280955	-1.916003	0.0555

R-squared	0.977908	Mean dependent var	21.87047
Adjusted R-squared	0.977867	S.D. dependent var	9.164939
S.E. of regression	1.363475	Akaike info criterion	3.460256
Sum squared resid	4017.440	Schwarz criterion	3.473370
Log likelihood	-3742.458	Hannan-Quinn criter.	3.465052
Durbin-Watson stat	2.167627		

Selection Summary

Added CAPA
Added PAMO
Added COPA

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 28: Stepwise Model with Smoothed Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:00
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2167 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Stepwise forwards
Stopping criterion: p-value forwards/backwards = 0.1/0.1
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.951297	0.015723	60.50352	0.0000
VIXSPOT(-1)	0.045829	0.015011	3.053015	0.0023
CAPA	-7.284614	1.206493	-6.037842	0.0000
DPAMO	1.915477	0.474262	4.038857	0.0001
DCOMA	-1.822812	0.594311	-3.067101	0.0022

R-squared	0.977974	Mean dependent var	21.87257
Adjusted R-squared	0.977934	S.D. dependent var	9.163345
S.E. of regression	1.361195	Akaike info criterion	3.456908
Sum squared resid	4005.865	Schwarz criterion	3.470016
Log likelihood	-3740.559	Hannan-Quinn criter.	3.461701
Durbin-Watson stat	2.161862		

Selection Summary

Added CAPA
Added DPAMO
Added DCOMA

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 29: Swapwise Model with Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:08
Sample (adjusted): 1/05/2007 8/28/2015
Included observations: 2017 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Swapwise - Max R-squared
Number of search regressors: 5
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.970642	0.016072	60.39388	0.0000
VIXSPOT(-1)	0.034104	0.015169	2.248337	0.0247
COMA	6.604348	1.657680	3.984092	0.0001
PCRALL	-0.276884	0.083587	-3.312528	0.0009
PAMO	2.454111	1.169999	2.097532	0.0361
PCR130	-0.149578	0.045152	-3.312776	0.0009
COPA	-7.773987	1.247284	-6.232730	0.0000

R-squared	0.979353	Mean dependent var	21.95816
Adjusted R-squared	0.979291	S.D. dependent var	9.277348
S.E. of regression	1.335067	Akaike info criterion	3.419304
Sum squared resid	3582.630	Schwarz criterion	3.438771
Log likelihood	-3441.368	Hannan-Quinn criter.	3.426449
Durbin-Watson stat	2.196451		

Selection Summary

Added CAPA
Added PCR160
Added PAMO
Added PCR130
Removed PCR160
Added PCRALL
Added COPA
Removed CAPA
Added COMA

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 30: Swapwise Model with Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:06
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2018 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Swapwise - Max R-squared
Number of search regressors: 5
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.971226	0.015992	60.73267	0.0000
VIXSPOT(-1)	0.033548	0.015107	2.220778	0.0265
CAPA	-7.790577	1.244724	-6.258877	0.0000
PCRALL	-0.276196	0.083601	-3.303729	0.0010
DPAMO	1.454177	0.779822	1.864756	0.0624
PCR130	-0.152782	0.044707	-3.417401	0.0006
DAMB	-0.367758	0.443869	-0.828528	0.4075

R-squared	0.979355	Mean dependent var	21.96038
Adjusted R-squared	0.979293	S.D. dependent var	9.275581
S.E. of regression	1.334750	Akaike info criterion	3.418828
Sum squared resid	3582.712	Schwarz criterion	3.438287
Log likelihood	-3442.597	Hannan-Quinn criter.	3.425969
Durbin-Watson stat	2.193323		

Selection Summary

Added CAPA
Added PCR160
Added DPAMO
Added PCR130
Removed PCR160
Added PCRALL
Added DAMB

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 31: Swapwise Model with Smoothed Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:08
Sample (adjusted): 1/09/2007 8/28/2015
Included observations: 2151 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Swapwise - Max R-squared
Number of search regressors: 5

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.944090	0.016639	56.74013	0.0000
VIXSPOT(-1)	0.052989	0.015390	3.443107	0.0006
COMA	4.610802	1.638831	2.813470	0.0049
PAMO	3.246259	1.134194	2.862171	0.0042
COPA	-7.375930	1.229145	-6.000861	0.0000
PCR130SM	0.099821	0.061778	1.615805	0.1063
PCRALLSM	-0.155378	0.142445	-1.090792	0.2755

R-squared	0.977881	Mean dependent var	21.91816
Adjusted R-squared	0.977820	S.D. dependent var	9.177609
S.E. of regression	1.366831	Akaike info criterion	3.466116
Sum squared resid	4005.479	Schwarz criterion	3.484580
Log likelihood	-3720.808	Hannan-Quinn criter.	3.472871
Durbin-Watson stat	2.184046		

Selection Summary

Added CAPA
Added PAMO
Added COPA
Removed CAPA
Added COMA
Added PCR130SM
Added PCRALLSM

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 32: Swapwise Model with Smoothed Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:05
Sample (adjusted): 1/09/2007 8/31/2015
Included observations: 2152 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Swapwise - Max R-squared
Number of search regressors: 5

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.949988	0.016733	56.77256	0.0000
VIXSPOT(-1)	0.047505	0.015485	3.067794	0.0022
CAPA	-7.422211	1.216276	-6.102408	0.0000
DPAMO	2.003212	0.481112	4.163710	0.0000
DCOMA	-1.995875	0.628284	-3.176706	0.0015
PCR130SM	0.107787	0.061620	1.749217	0.0804
PCRALLSM	-0.122359	0.143189	-0.854526	0.3929

R-squared	0.977949	Mean dependent var	21.92025
Adjusted R-squared	0.977887	S.D. dependent var	9.175989
S.E. of regression	1.364502	Akaike info criterion	3.462704
Sum squared resid	3993.703	Schwarz criterion	3.481161
Log likelihood	-3718.869	Hannan-Quinn criter.	3.469456
Durbin-Watson stat	2.177356		

Selection Summary

Added CAPA
Added DPAMO
Added DCOMA
Added PCR130SM
Added PCRALLSM

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 33: Combinatorial Model with Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:13
Sample (adjusted): 1/05/2007 8/28/2015
Included observations: 2017 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Combinatorial
Number of search regressors: 5
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.970642	0.016072	60.39388	0.0000
VIXSPOT(-1)	0.034104	0.015169	2.248337	0.0247
CAPA	-6.604348	1.657680	-3.984092	0.0001
PAMO	2.454111	1.169999	2.097532	0.0361
PCR130	-0.149578	0.045152	-3.312776	0.0009
PCRALL	-0.276884	0.083587	-3.312528	0.0009
COPA	-1.169639	1.365351	-0.856658	0.3917

R-squared	0.979353	Mean dependent var	21.95816
Adjusted R-squared	0.979291	S.D. dependent var	9.277348
S.E. of regression	1.335067	Akaike info criterion	3.419304
Sum squared resid	3582.630	Schwarz criterion	3.438771
Log likelihood	-3441.368	Hannan-Quinn criter.	3.426449
Durbin-Watson stat	2.196451		

Selection Summary

Number of combinations compared: 126

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 34: Combinatorial Model with Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:43
Sample (adjusted): 1/05/2007 8/31/2015
Included observations: 2018 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Combinatorial
Number of search regressors: 5
Note: final equation sample is larger than stepwise sample (rejected regressors contain missing values)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.971226	0.015992	60.73267	0.0000
VIXSPOT(-1)	0.033548	0.015107	2.220778	0.0265
CAPA	-7.790577	1.244724	-6.258877	0.0000
DPAMO	1.454177	0.779822	1.864756	0.0624
PCR130	-0.152782	0.044707	-3.417401	0.0006
PCRALL	-0.276196	0.083601	-3.303729	0.0010
DAMB	-0.367758	0.443869	-0.828528	0.4075

R-squared	0.979355	Mean dependent var	21.96038
Adjusted R-squared	0.979293	S.D. dependent var	9.275581
S.E. of regression	1.334750	Akaike info criterion	3.418828
Sum squared resid	3582.712	Schwarz criterion	3.438287
Log likelihood	-3442.597	Hannan-Quinn criter.	3.425969
Durbin-Watson stat	2.193323		

Selection Summary

Number of combinations compared: 126

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 35: Combinatorial Model with Smoothed Put-Call Ratios and Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:14
Sample (adjusted): 1/09/2007 8/28/2015
Included observations: 2151 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Combinatorial
Number of search regressors: 5

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.944090	0.016639	56.74013	0.0000
VIXSPOT(-1)	0.052989	0.015390	3.443107	0.0006
CAPA	-4.610802	1.638831	-2.813470	0.0049
PAMO	3.246259	1.134194	2.862171	0.0042
COPA	-2.765128	1.332741	-2.074768	0.0381
PCR130SM	0.099821	0.061778	1.615805	0.1063
PCRALLSM	-0.155378	0.142445	-1.090792	0.2755

R-squared	0.977881	Mean dependent var	21.91816
Adjusted R-squared	0.977820	S.D. dependent var	9.177609
S.E. of regression	1.366831	Akaike info criterion	3.466116
Sum squared resid	4005.479	Schwarz criterion	3.484580
Log likelihood	-3720.808	Hannan-Quinn criter.	3.472871
Durbin-Watson stat	2.184046		

Selection Summary

Number of combinations compared: 126

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 36: Combinatorial Model with Smoothed Put-Call Ratios and Deep Implied Volatility Skew Variables

Dependent Variable: _1FUTURE
Method: Stepwise Regression
Date: 05/02/16 Time: 14:12
Sample (adjusted): 1/09/2007 8/31/2015
Included observations: 2152 after adjustments
Number of always included regressors: 2
Number of search regressors: 9
Selection method: Combinatorial
Number of search regressors: 5

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
_1FUTURE(-1)	0.949988	0.016733	56.77256	0.0000
VIXSPOT(-1)	0.047505	0.015485	3.067794	0.0022
CAPA	-7.422211	1.216276	-6.102408	0.0000
DPAMO	2.003212	0.481112	4.163710	0.0000
DCOMA	-1.995875	0.628284	-3.176706	0.0015
PCR130SM	0.107787	0.061620	1.749217	0.0804
PCRALLSM	-0.122359	0.143189	-0.854526	0.3929

R-squared	0.977949	Mean dependent var	21.92025
Adjusted R-squared	0.977887	S.D. dependent var	9.175989
S.E. of regression	1.364502	Akaike info criterion	3.462704
Sum squared resid	3993.703	Schwarz criterion	3.481161
Log likelihood	-3718.869	Hannan-Quinn criter.	3.469456
Durbin-Watson stat	2.177356		

Selection Summary

Number of combinations compared: 126

*Note: p-values and subsequent tests do not account for stepwise selection.

Panel 37: Independent Variables included in the Predictive Models

	VIX Future (t-1)	VIX Spot (t-1)	PCR130	PCRALL	COMA (t)	DCOMA (t)	PAMO (t)	DPAMO (t)	CAPA (t)
Model 1	X	X							
Model 2	X	X	X						
Model 3	X	X		X					
Model 4	X	X	X	X					
Model 5	X	X			X				X
Model 6	X	X				X			X
Model 7	X	X					X		X
Model 8	X	X						X	X
Model 9	X	X	X		X				X
Model 10	X	X	X			X			X
Model 11	X	X	X				X		X
Model 12	X	X	X					X	X
Model 13	X	X		X	X				X
Model 14	X	X		X		X			X
Model 15	X	X		X			X		X
Model 16	X	X		X				X	X
Model 17	X	X	X	X	X				X
Model 18	X	X	X	X		X			X
Model 19	X	X	X	X			X		X
Model 20	X	X	X	X				X	X