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Modeling Intraday Implied Volatility: Evidence From EURO STOXX 50

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Juuso Tikanoja
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MODELING INTRADAY IMPLIED VOLATILITY:

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Juuso Tikanoja
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Aalto University School of Business **Abstract**
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Juuso Tikanoja

MODELING INTRADAY IMPLIED VOLATILITY: EVIDENCE FROM EURO STOXX 50

PURPOSE OF THE STUDY

The objective of this thesis is to study intraday implied volatility with high-frequency observations. Specifically, I study if systematic intradaily and weekly patterns exist in implied volatility of EURO STOXX 50. Furthermore, I study if the implied volatility can be modeled using the possible patterns and time series econometric methods. Additionally, I study if the modeling can provide abnormal economic profits.

DATA AND METHODOLOGY

The dataset includes over 110 000 observations from VSTOXX, the implied volatility index of EURO STOXX 50 from January 2012 to the end of November 2012. Additionally, I acquire similar time-series of several financial instruments. To test the hypotheses, I study patterns with means and variances of VSTOXX. In addition, I model the data with ARMA family models and with several variables. Furthermore, I try to take advantage of possible patterns in intradaily/weekly implied volatility and use dummy variables in the modeling.

RESULTS

The empirical results of this thesis show that both intradaily and weekly patterns exist in implied volatility. Three possible reasons for the patterns were found: systematic patterns because of the VSTOXX formula misspecification, patterns driven by stock markets and patterns driven by traders. Modeling of implied volatility is found to be possible. ARMA models perform the best with the dataset. Several economic/financial variables are significant. Also, the weekday/time dummies were significant. However, when measuring the directional accuracy of the models, it seems that only ARMA model can forecast the direction and adding external variables is not useful. Even though proper trading simulation was not conducted, it seems that abnormal profits would not be created with models

KEYWORDS

Implied volatility, options, modeling, intraday, patterns, VSTOXX, EURO STOXX 50

Aalto-yliopiston kauppakorkeakoulu **Tiivistelmä**
Pro gradu-tutkielma **11. helmikuuta 2013**
Juuso Tikanoja

IMPLISIITTESEN VOLATILITEETIN MALLINNUS

TUTKIMUKSEN TAVOITTEET

Pro Gradu-tutkielmani tavoitteena on tutkia päivän sisäistä implisiittistä volatiliteettia. Ensin tutkin yksityiskohtaisesti EURO STOXX 50 implisiittisen volatiliteetin systemaattista käyttäytymistä päivä- ja viikkotasolla. Tämän jälkeen pyrin mallintamaan implisiittistä volatiliteettia päivän sisällä. Lopuksi vielä tutkin mallien paremmuutta ja mahdollisuuksia epänormaaleihin tuottoihin.

LÄHDEAINEISTO

Lähdeaineisto koostuu yli 110 000 EURO STOXX 50:nimplisiittisen volatiliteetti-indeksin VSTOXX:n havainnosta. Lisäksi hankin samalle aikasarjalle aineiston moneen rahoitusinstrumenttiin. Aikasarjan ajanjakso on vuoden 2012 tammikuusta marraskuun loppuun. Testatakseni hypoteeseja tutkin ensin systemaattista käyttäytymistä VSTOXX havaintojen keskiarvoilla ja variansseilla päivän sisällä. Lisäksi mallinnan VSTOXX:ia ARMA perheen aikasarjamalleilla. Pyrin parantaa aikasarjamalleja lisäämällä systemaattisesta käyttäytymisestä johdettuja muuttuja sekä rahoituksellisilla selittävillä muuttujia.

TULOKSET

Tämän tutkimuksen empiiriset tulokset tukevat päivittäisen ja viikoittaisen systemaattisen käyttäytymisen löytymistä implisiittisessä volatiliteetissä. Systemaattisuutta voidaan selittää VSTOXX:n laskentamallin systemaattisilla virheillä, osakemarkkinoilta heijastuvana ja/tai sijoittajien ostojen ajoittamisesta johtuvana. Päivän sisäisen implisiittisen volatiliteetin mallintaminen onnistuu parhaiten ARMA malleilla. Useat taloudelliset ja rahoitukselliset muuttujat sekä kellon aika ja viikonpäivä muuttujat ovat tilastollisesti merkittäviä. Kuitenkaan ulkopuoliset muuttujat eivät kykene ennustamaan implisiittisen volatiliteetin muutoksen suuntaa ”kolikon heittoa” paremmin. ARMA mallit pystyivät ennustamaan implisiittistä volatiliteettiä paremmin. Epänormaalien tuottojen saaminen malleilla vaikuttaa kuitenkin mahdottomalta.

AVAINSANAT

Implisiittinen volatiliteetti, optiot, mallintaminen, päivän sisäinen, VSTOXX, EURO STOXX 50

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1. Introduction

1.1 Background and motivation

Implied volatility (IV)[1] as a concept has spread to the general public since the VIX index (IV index of S&P 500) has gained wide recognition among all investors as fear gauge. IV is considered to be the best estimate for future volatility, and thus investors follow it closely. Earlier literature has concluded that IV is a biased forecast of volatility and has predictive power for future volatility. Additionally, implied volatility is the second most important price determinant of options other than the price of the underlying itself. Thus, it is essential part of any option traders' work. In addition, many hedge funds and proprietary traders in investment banks take positions on pure implied volatility. Generally these traders are more interested in daily or weekly forecasts. However, the growing algorithmic trading is certainly interested in trading IV with high-frequency algorithms. Volatility futures, which aim to make pure volatility tradable, have facilitated volatility trading. The volatility futures were introduced during the last decade for many implied volatility indices. After a slow start, at least in Europe, their volume has significantly picked up. Lately, over 20 000 contracts of VSTOXX futures, which are used in this research, have been traded daily. Futures of the VIX index are even more popular with daily trading volume of over 100 000 contracts.

During the last few decades implied volatility has become a common topic in academic literature. Most of the earlier literature covers only attribute of IV in forecasting future realized volatility. Nevertheless, implied volatility, its modeling and patterns, is an area which has remained relatively unexplored. At least, when considering the immense literature on historic volatility modeling and forecasting with general autoregressive conditional heteroskedasticity (GARCH) models. However, there are a few studies which examine forecastability of IV. One of the first ones is Harvey and Whayley (1992). They find implied volatility to be predictable, but state that trading profits would dissolve as transaction costs were reckoned in. When speaking of more recent evidence on predictability, for example Brooks and Oozer (2002) and Ahoniemi (2009) come to same conclusion as Harvey and

[1] In this paper volatility refers to implied volatility. Realized historic volatility, i.e. standard deviation of an asset, is always referred with real, realized or historic volatility.

Whaley. These studies find ARMA (autoregressive moving average) family time series models to be good fit for IV series. Implied volatility series are stationary. Additionally, IV series are usually very persistent time series, i.e. observations display high autocorrelation. Hence, the ARMA models, which consist of autoregressive coefficients (AR) and moving average of error term coefficients (MA), are usually a good fit for IV series. Nevertheless, all the previous studies use straddle option strategy to trade volatility. Straddles used to be the most effective way to trade volatility with options, but today when volatility futures have been introduced, it is clear that this is not the case anymore. Straddles are discussed more thoroughly in section 2.3.1.

Most financial activity variables display pronounced intradaily and weekly patterns. In modern financial markets, understanding intraday patterns is in central part. The patterns might provide some trading opportunities for investors or at least indicate the best moment during the trading day to execute orders. Previous literature has found that IV tends to increase clearly on Mondays, then rise slightly from Tuesday to Thursday and decrease on Fridays. However, further investigations on implied volatility patterns have not been conducted. Several studies report day-of-the-week effects and intradaily patterns in option (see, e.g. Stephan and Whaley, 1990) and stock markets (see, e.g. Harris, 1986). These similar patterns should be found in some form also in IV. The patterns are not similar in stock markets and option markets. Thus, if IV actually forms systematic patterns, it is not obvious that which one of the two patterns, IV patterns should follow – or does it form its own patterns. IV is central pricing element of options, but on the other hand IV of stock index is measure for expected stock market risk. Thus, there should be causality between IV and both of the markets. Finding out which one is the leading determinator hence also answers the question of the role of IV: is implied volatility only a pricing element of options or also a good fear gauge.

Another notable thing is that all relevant earlier studies have been made with data before the Lehman collapse, when IV peaked to all-time highs all over the world. Additionally, "new volatility" has lately been common topic in financial and economic discussion. The people that believe in this phenomenon state that western economies have entered to an era where the volatility of both economy and financial markets is higher than what we are used to during the previous decades. Whether this is the new reality or not, is not exactly the topic of this study.

However, it is clear that the average volatility has been higher than before since late 2008. This anyhow brings a burning and interesting aspect to this study.

This study will, according to my knowledge, be the first one to examine and model intraday implied volatility. I will first examine the day-of-the-week effects and intraday patterns of implied volatility. Secondly, I model intraday VSTOXX, which is the implied volatility index of EURO STOXX 50. I use two datasets of VSTOXX: one with 1-minute intervals and another with 10-minute intervals. Using directly an implied volatility index, instead of calculating IVs from option data, will circumvent some of the methodological problems with option pricing models. For example, the most used option pricing, the Black-Scholes model (B-S model) has certain shortcomings that are widely recognized, such as assuming volatility to be constant throughout the lifetime of an option. Naturally using IV index also makes the study a lot easier not having to inversely calculate the volatility forecasts. Additionally, I will include weekday and hour dummies, based on the possibly discovered IV patterns, into models. The models are then compared with out-of-sample forecasting directional accuracies. In this thesis implied volatility is a subject, not an object. Earlier literature has used IV to understand other phenomenon, but my aim is to understand intraday implied volatility.

The pattern findings and the forecasts can be used for several purposes. First, traders such as the proprietary traders can profit if they have a view on the direction of IV by trading directly with derivatives. Secondly, option traders/investors can also benefit from the forecasts, because IV is essential pricing instrument of options. Additionally, even if the forecasts were not good, the patterns can be used to timing option purchases and sales. Furthermore, the role as a risk factor has stand out during the last decade. Hence, IV forecasts can be seen as forecasts for risk as well.

1.2 Contribution to existing literature

This study extends on previous research on implied forecasting in several ways. First and foremost, my data consist of high frequency intraday observations of the EURO STOXX 50 implied volatility index VSTOXX. Intraday observations have not been used in related studies before. The intraday dataset allows this study to extend existing literature on weekday effects in IV, but also to study intraday patterns. Additionally, I will define whether the day-of-the-week effects actually occur during the trading or non-trading period of the days. Secondly, I will use the findings of possible patterns to model implied volatility in EURO STOXX 50 with time series econometrics. When it comes to earlier literature, only Konstantinidi et al. (2007) model VSTOXX. However, VSTOXX is only in a side role in that paper, while the VIX is the main subject. The majority of earlier literature has studied the American VIX index. Thus this study will contribute useful info on both modeling intraday IV and modeling VSTOXX. After all, even though the basic idea and calculation is similar as in the VIX, the two indices have varied surprisingly much in the past. Furthermore, I am going to examine the intraday patterns of IV also in the modeling section, e.g. regressing hour dummy variables on the VSTOXX. Thirdly, I will study trading opportunities which profitable IV forecasts possibly provide. I use volatility futures, which are obvious choice for implied volatility trading. Hence, this study also sheds light on economic profitability of intraday IV forecasts.

1.3 Research questions

This thesis studies patterns and modeling of implied volatility of EURO STOXX 50. I use high-frequency VSTOXX index observations as a dataset. Methodology for detecting intraday patterns is similar as in Harris (1986), which studies intraday patterns of stock returns. I am trying to detect both weekly and intradaily patterns. Furthermore, the methodology for modeling IV follows mostly studies such as Harvey and Whaley (1994), Konstantinidi et al. (2007), Ahoniemi (2009) and Brooks and Oozer (2002). The models to be tested are ARMA family models and GARCH models. Additionally I use external explanatory variables independently and together with ARMA models. The following research questions are examined:

- Are there any day-of-the-week effects in the VSTOXX?
- Are there any intraday patterns in the VSTOXX?
- Can the implied volatility of EURO STOXX 50 be modeled and forecasted with high frequency intraday data?
- Can the models provide accurate directional forecasts for the volatility changes?

Additionally, I try to find out whether these models might be able to provide economic profits when used in futures trading. I use a VSTOXX futures dataset for finding out:

- Can the models provide economic profits in trading simulation?

1.4 Main findings

Intraday patterns do exist in implied volatility. The patterns are consequent of either model specification problems of IV or driven by stock market patterns. IV declines towards each trading day, because of the VSTOXX formula do not update dynamically time-to-maturity part in the formula during the trading day. Additionally, IV declines during the first hour of trading, and then slightly rises for several hours during the trading day before the close. Inclining IV in the middle of trading day can be explained by stock prices. Stock prices follow U-shaped pattern. The decreasing stock prices then reflect to higher IV at the bottom of the "U". IV then declines again before the close, which is consistent with rising stock prices at the end of trading. Volatility of IV is very low during the first 30 minutes of the trading day, which is consistent with earlier literature on option volumes and volatilities studies (see, e.g. Stephan and Whaley, 1990).

Day-of-the-week effects also exist in implied volatility. Measuring close-to-close I confirm the findings of earlier IV studies: IV tend rise on Mondays, then continue to rise slightly Tuesday to Thursday, but then drastically decline on Friday. The time-to-maturity problem is emphasized on Fridays, because of two days of inactivity over the weekend. Thus, IV declines on average the whole day on Fridays. When examining more closely it is obvious that intraday changes are not similar. Majority of the weekly implied volatility patter described earlier seems to actually occur during the non-trading periods. The declining IV on Fridays is obvious also during the trading day, but for instance on Mondays the mean change over the whole trading day is actually negative. Nevertheless, overnight changes were found to be smaller than the changes during trading days. Similar results regarding the magnitude of changes overnight have been earlier reported in stock market pattern studies. Additionally, on Thursdays IV decreases close-to-close and open-to-close. The weekend effect seems to start already on Thursday afternoon.

ARIMA(1,1,1) model was found to be the best fit for the data, when considering residuals and directional accuracy of the models. The directional accuracy is the most important indicator, because the purpose of these models is to forecast directional changes of IV. Adding any kind of external variables into models did not improve models – and in many cases the models actually deteriorated. All variables, except EUR/CHF currency rate variable, were significant when regressed on VSTOXX. Additionally, several hour and weekday dummies were also found significant. However, when several economic and ARMA variables were included, the models did not perform well anymore. GARCH extensions, which have been found useful in e.g. Ahoniemi (2009), do not provide any extra for the models. This is in line with statistical properties of my dataset; ARCH tests, squared residuals and Durbin-Watson statistics indicate that ARCH effects do not exist.

Trading simulation does not work with data available on Bloomberg, because there are not price observations for each minute. Thus, a robust trading simulation cannot be conducted, but I estimate the models with other methods. I conducted other trading simulations which indicate that ARIMA(1,1,1) model would provide economic profits, even when trading costs are accounted. However, when studying the VSTOXX futures data, and especially bid-ask spreads, it seems clear that profits cannot be generated. The bid-ask spread is much larger than mean change on 1-minute or 10-minute interval. Thus, in average situation the model would not be profitable even if it forecasted the direction of IV perfectly. And when considering that earlier studies have not found trading to be profitable on daily intervals, although the trading methods have been poorer, the conclusion seems pretty robust.

1.5 Limitations of the study

The main limitations of the study are related to data. While the data has over 100 000 observations, which is more than sufficient for time series modeling, number of trading days is pretty low. Thus, this is reflected in low number of observations in IV pattern tests. However, compared to previous studies the sample size is similar to what has been used in e.g. detecting intraday patterns for stock markets. Also, the significance of the results for intraday and weekly patterns suggests that they are robust despite small sample sizes.

In addition, there is no intraday data available for some of the explanatory variables. For instance, EURIBOR interest rates are calculated only daily. EURIBOR rates have been used in some previous studies (see, e.g. Konstantinidi et al., 2007) in economic variables models to forecast IV.

Third limitation is related to the trading simulation. The dataset of VSTOXX futures quotes do not contain observations for all minutes. Price quotes are only available for every fifth minute and bid/ask quotes are available for every second minute on average. Thus, a proper trading simulation cannot be conducted. I was forced to use more qualitative methods for finding out the economic significance of the forecasts. The methods are discussed more carefully in section 5.2.3. However, the trading simulation would have had only a side role in the thesis. The main reason for conducting one is to rank models and give suggestive results for economic significance of the models. Directional accuracy is also a robust method to rank the model. Thus, this limitation is not of the importance in this study.

1.6 Structure of the paper

This paper is structured as follows. This first part has now introduced the topic, the research questions and the main results. In the following section, I introduce theory and previous literature of implied volatility. The third section introduces the hypotheses to be tested in the thesis. Then in the fourth part I introduce the data sets and methodology used in the study. The fifth part reports the results and analysis done on basis of them. The last sixth part concludes the research questions and the results of the hypotheses.

2. Theory and previous literature

In this section, I familiarize theory and previous literature related to this study. Firstly, I introduce implied volatility and previous literature on implied volatility and its role in the financial markets. Additionally, I present earlier literature on forecasting of implied volatility and implied volatility as forecast for future volatility. Secondly, I introduce the earlier literature of intradaily and weekly patterns in option and stock markets. These patterns provide base theories for detecting patterns in implied volatility. Thirdly, I will shortly explain earlier studies and theories for volatility trading.

2.1 Implied volatility

2.1.1 Calculation of implied volatility

Volatility is a measure for variation of price of a financial instrument over time. Historic volatility is a measure of instruments past performance. The most common volatility, annualized volatility, is calculated as a standard deviation of equity´s yearly logarithmic changes. Volatility is used to quantify the risk of the asset – the larger the standard deviation, the larger the risk. Normally options are not trading at the exact price calculated with historic volatility, but the markets determine the volatility at the current market situation. This volatility is called implied volatility. Thus, IV is the expected volatility in the future.

Implied volatility can be calculated with Black & Scholes option pricing model (Black and Scholes, 1973) from option prices. When price of an option is known, implied volatility can be calculated by placing all the other data, but the volatility in the model. Pricing of all financial instruments is based on the expectations, not on the past. IV is calculated from prevailing option prices. The pricing model depends upon only five variables and probability of the changes in underlying assets is not needed.

Call option prices are calculated with Black & Scholes option pricing model. To calculate the price of an option you need the following: strike price (=K), current share price (=S), time to maturity (=T-t), volatility of underlying (=σ), annualized risk-free interest rate (=r). In this calculation risk-free interest rate, which fluctuates and is not set such as for example strike price, is given from outside the model:

$$C(S,t) = N(d_1)S - N(d_2)\,Ke^{-r(T-t)} \tag{1}$$

Where,

$$d_1 = \frac{ln\left(\frac{S}{K}\right)+\left(r+\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}} \tag{2}$$

$$d_2 = \frac{ln\left(\frac{S}{K}\right)+\left(r-(\sigma^2/2)\right)(T-t)}{\sigma\sqrt{T-t}} = d_1 - \sigma\sqrt{T-t} \tag{3}$$

2.1.2 Shortcomings of Black & Scholes model implied volatility

It has been well documented that on any given date, implied volatilities depend on the strike price and maturity of the option under scrutiny giving rise to a non-flat implied volatility surface. There are two widely recognized assumptions that Black & Scholes model makes which are not consistent with what is observed in financial markets (Ahoniemi, 2009). Firstly, the model expects volatility to stay constant through the whole life-time of an option. Secondly, logarithmic returns of underlying assets are assumed to follow a normal distribution[2]. These assumptions lead to an effect called volatility smile or volatility skew. It is a pattern in which at-the-money[3] options tend to have lower implied volatilities than in- or out-of-the-money options. Equity options traded in American markets did not show a volatility smile before the crash of 1987 but began showing one afterwards. Due to these shortcomings, interest on developing option pricing model, that could account for stochastic volatility and thus reflect market prices of options more accurately, has aroused (see, e.g. Hull and White (1987); Harvey et al. (1994)). However, Black & Scholes model still remains to be the most widely recognized choice for obtaining IV (Fleming et al., 1995). Jorion (1995) also argues that the use of stochastic volatility models requires the estimation of additional parameters, which naturally introduces an additional potential source of error. Furthermore, Hull and White (1987) state that Black-Scholes implied volatilities are least biased for at-the-

[2] Aggregate stock market returns display negative skewness, the propensity to generate negative returns with greater probability than suggested by a normal distribution. Numerous studies have aimed to explain this (see, e.g. Fama, 1965).
[3] At-the-money (ATM) option is an option which strike price is equal to price of underlying security. In-the-money (ITM) means that strike is lower than the asset price in case of call option (higher in put option). Out-of-the-money (OTM) option is the opposite of In-the-money option. ATM option prices have the highest vega, i.e. they are the most sensitive to changes in implied volatility.

money short-term options, thus errors in IV estimates stemming from shortcomings of B-S model can be minimized by using ATM options. Hentschel (2003) remarks that implied volatility calculated by inverting the Black-Scholes formula is subject to considerable error when option characteristics are observed with plausible errors. Especially for options away from the money, large changes in volatility produce small changes in option prices. Conversely, small errors in option prices and other option characteristics produce large errors in implied volatilities. In the presence of small measurement errors, unobserved truncation of option prices that violate lower bounds for absence of arbitrage can also lead to systematic volatility smiles, even if all the assumptions in B-S model actually holds.

Additionally, the smile has been tested empirically in trading simulations trying to take advantage of the possible market inefficiency. Ederington and Guan (2002) provide evidence that B-S model can be correct despite the existence of volatility smile. Using stock index options data, they test and reject the hypothesis that the smile in stock index option prices is wholly due to inappropriate distributional assumptions by the Black-Scholes option pricing model. They argue that the true smile persists despite these substantial pre-transaction-cost profits, because maintaining the trading portfolio’s original low risk profile requires frequent re-balancing, which quickly eats away the profits. Consequently, the smile is not evidence of market inefficiency.

2.1.3 Macroeconomic changes and abnormal market behavior

Early literature of implied volatility covers mainly two topics. First category examines if there is relationship between IV changes and macroeconomic changes. Second category studies IV as a signal of abnormal market behavior. Schmalensee and Trippi (1978) examine the mechanism through which the market revises its expectations of stock volatility. This knowledge could add to our understanding of speculative markets. Grasping the mechanism seems to be hard, and the findings arouse more questions than they seem to answer. For example Schmalensee and Trippi think that investors´ exposure to aggregate or average data relating to the stock market as a whole might serve to affect their expectations of individual stocks´ volatilities. However, no strong evidence for such effects is encountered. They also have strong belief in hypothesis stating that changes in IV should be related to historical stock-specific volatility. Still, they find out no support for this in the data. Franks and

Schwartz (1992) consider various financial and real variables that may be correlated with innovations in expected volatility. They find that leverage could be a significant explanatory variable, but that it cannot be the only one. As a result, they test for other variables that may explain changes in the volatility of the underlying assets. They find inflation and long-term interest rates to be significant additional explanatory variables. Finally, Franks and Schwarz find that many of the innovations in volatility do not persist for very long periods. The result has important implications for how we estimate volatilities over varying time horizons and for the impact of volatility changes on the market´s estimated risk premium.

2.1.4 Forecast of future realized volatility and information content

Bulk of the IV literature covers the question whether IV is an adequate prediction for future realized volatility. Generally speaking, these studies have concluded that IV is a biased forecast of volatility and has predictive power for future volatility. Many studies have found that implied volatility includes all information available.

Blair et al. (2001) answer some empirical questions for the S&P100 index. Most importantly, the question about how does the predictive quality of volatility forecasts from ARCH models, that use daily index returns and/or intraday returns, compare with forecasts from models that use information contained in implied volatilities? In-sample analysis finds no evidence of additional information in daily index returns, which is not provided by implied volatility. Out-of-sample analysis show that VIX provides more accurate forecasts than either low-frequency or high-frequency index returns. Furthermore, these results are found regardless of the definition of realized volatility and the horizon of the forecasts. These results are in-line with many previous studies (see, e.g. Day and Lewis, 1992; Jorion, 1995).

Simon (2003) examines the VXN, a volatility index for Nasdaq 100 options, over a period from before and after the Internet “bubble”. If the VXN is the market’s best estimate of the future volatility of the Nasdaq 100 index, it should be an unbiased forecast of subsequent realized volatility. But if the VXN represents a “fear index,” it will reflect variations in investors’ emotions, e.g. rising after a sharp market drop. Simon finds that even after correcting for the effect of a little-known built-in bias in the way it is constructed, the VXN averages about 7-1/2 percentage points higher than subsequent realized volatility. It also shows a strong asymmetrical response to positive and negative index returns, as has been found in other implied volatility studies. A GARCH model fitted to the returns on the actual index also reveals an asymmetrical response of volatility to returns, but much smaller than for the VXN. The evidence suggests that implied volatilities from options on the Nasdaq 100 index reflect the stochastic properties of the index itself, but they also show behavior that appears to be more closely related to investor sentiment.

Jiang and Tian (2005) perform tests of the informational efficiency of the option market using an alternative implied volatility measure that is independent of option pricing models. Jiang and Tian derive IV entirely from no-arbitrage conditions. Additionally, they do not only use at-the-money options which are generally used in IV researches. Their findings from the SPX options support the hypothesis that the model-free implied volatility subsumes all information contained in both B-S implied volatility and historic realized volatility. Additionally, they find that it is more efficient forecast for future realized volatility.

Carr &Wu (2006) examine the major differences between the old and the new volatility indexes (VIX and VXO), and discuss the practical motivations behind the recent switch. They also analyze historical behavior of the new volatility index and how it interacts with stock index returns and realized volatilities. Carr and Wu obtain several interesting findings analyzing 15 years of index data. For instance, the new index is on average some 2% higher than the bias-corrected older version. However, the sample average of the 30-day realized volatility on SPX is 0.66% lower than that of OEX. They also study VIX behavior around FOMC (Federal Open Market Committee of Federal Reserve System) meeting days, *i.e*. the days when monetary policy decisions such as federal funds target rate changes are often announced. They find that the volatility index increases prior to the meeting but drops rapidly after the meeting. Moreover, they find that the VIX can predict movements in future realized variance and that GARCH volatilities do not provide extra information once the VIX is included as a regressor.

2.1.5 Modeling and forecasting implied volatility

Clear minority of studies are concentrating on forecasting IV. The earlier literature is pretty unanimous that IV can be forecasted. However, almost all studies find that economic profits in trading simulations after transaction costs are not provided by the models. Thus, the predictable patterns overall are found only from a statistical point of view. Ahoniemi (2009) models four different time series of implied volatility. In the first essay Ahoniemi uses an ARIMA model to model the VIX index. The second essay estimates two-regime multiplicative error models for the IV of options on the Japanese Nikkei 225 index. The third essay investigates the joint modeling of call and put IVs with a two-regime bi-variate multiplicative error model. The fourth essay models the IV of options on the USD/EUR exchange rate. The overall finding is that implied volatility can indeed be forecasted, and its modeling can benefit from a new class of time series models: multiplicative error models. Additionally, it is often beneficial to model IV with two (or more) regimes to allow for periods of relative stability and periods of higher volatility in markets, even though the difference with more traditional ARMA modeling is not large. The directional accuracy of forecasts in trading simulations in all four models is above 50% (between 58.4% and 72.2%). However, Ahoniemi does not run trading simulation to find out the possible usage of the models for trading purposes. The simulations are done only to rank the models and thus profitability of the model is not examined. Moreover, the simulations are executed with straddle positions, which is not anymore the best possible strategy to trade volatility (this will be further discussed in section 2.3). The first essay on forecasting VIX is the one that is closest to this paper in nature. Both studies model and forecast time series of an implied volatility index with ARMA and GARCH models. However, besides the underlying of the dataset, these two studies differ from each other by interval of observations.

Konstantinidi et al. (2007) examine forecasting ability of five models used in earlier researches with seven European and American IV indices. This is the only relevant study that has modeled VSTOXX or volatility of EURO STOXX. They model daily observations of VSTOXX during the period of February 2, 2001 to September 28, 2007. Konstantinidi et al. (2007) find ARIMA (1,1,1) model to fit the data, but they do not perform any trading simulations for the VSTOXX, since they are only concentrating in VIX in their simulations. Additionally they suggest that principal component analysis (PCA) also fit somewhat well with only VSTOXX and VCAC, the volatility index of French CAC 40 index, but not with the rest of the five IV indices. In-sample performance in the daily horizons case, the majority of implied volatility indices cannot be predicted point-wise in a statistical sense. In the monthly horizons case, the model with economic variables as predictors performed better, and gave positive results on predictability for example of the VIX. However, the out-of-sample statistical performance of the considered models is not superior to that of the random walk model. In line with the statistical evidence, the trading games do not generate significant riskadjusted profits once transaction costs are taken into account in both the daily and monthly horizons. Results indicate that CBOE volatility futures markets are informational efficient. Yet, it is notable that the trading experiment was done with VIX futures instead of e.g. S&P 500 options which have been used in other studies.

Harvey and Whaley (1992) and Brooks and Oozer (2002) share pretty much the same structure as in Ahoniemi´s research. Harvey and Whaley model IV of S&P100 options while Brooks and Oozer model IV of options on long gilt futures. Also these two papers select a time series model for IV series and calculate IV forecasts. Both of the studies conclude that future volatilities are in fact predictable. However, in their out-of-sample trading test with trading strategy based on the volatility forecasting, no economic profits are generated after transaction costs. In both studies buy-or-sell strategies are used in the trading simulation, which is not the best strategy when trading volatility.

Noh et al. (1994) is one of few relevant researches to state that GARCH model can create profit in excess of transaction costs. They carry through a simulation with near-the-money straddles of S&P 500 and included transaction cost of USD0.25 per straddle. However, the data used in the research is from years between 1986 and 1991. The financial markets and especially volatility were very different back then, so the results are at least debatable nowadays.

Besides of these studies there are, according to my knowledge, only two, unpublished studies that share somewhat same structure and methodology as in this paper. Fernandes et al. (2007) perform a thorough statistical examination of the time series properties of the VIX index. They run a series of preliminary analyses, and find results which suggest that there is some long-range dependence in the VIX index. The out-of-sample analysis evince that the linear ARMA and ARFIMA models perform very well in the short run and very poorly in the long-run, whereas the smooth transition autoregressive trees (START) model entails by far the best results for the longer horizon, despite of failing at shorter horizons. In contrast, the HAR-type models entail reasonable relative performances in most horizons. Finally, Fernandes et al. (2007) also show how a simple forecast combination brings about great improvements in terms of predictive ability for most horizons. Aboura (2003) proposes a precise description of volatility spillovers based on the international transmission of implied volatility. She examines the possible interactions between returns and implied volatility, and between implied volatilities belonging to different markets, using three implied volatility indexes: the

French VX1, the German VDAX and the American VIX. They obtain quite interesting results, concerning the impact of news on the implied volatility behavior and also on the interaction between implied volatility and realized volatility. For example when it comes to the impact of negative information on the implied volatility since she observe that the VX1 react strongly on the first day while the VDAX reaction spans over the two first days.

2.2 Weekly and intradaily patterns

Weekly and intradaily patterns of stocks and options have been widely studied during last three decades. So far, implied volatility patterns have not been examined thoroughly. Many earlier papers find IV to exhibit weekly seasonality (see, e.g. Harvey & Whaley, 1992; Brooks and Oozer, 2002; Ahoniemi, 2009). Implied volatility tends to rise on Mondays, fall slightly on Tuesdays, Wednesdays and Thursdays and then drop more drastically on Fridays. Previous literature has studied only close-to-close returns and it has not answered e.g. weather the Monday rise actually occurs during the weekend. Additionally, earlier studies do not study intraday data of IV at all. Thus, I will now introduce stock market and option market patterns. Both of these patterns can be used to benchmark for IV patterns as well.

2.2.1 Stock market patterns

One of the most well-known financial and the oldest market phenomenon is the weekday effect, in which stock returns on Mondays are often significantly lower than those of the immediately preceding Friday. Already Fama (1965) found that variance of Monday's returns is about 20% greater than other daily returns. However, the effect was actually already discussed in Fields (1931). Gibbons and Hess (1981) study the traditional distributional assumption regarding the returns on a financial asset specifies, which state that the expected returns are identical for all days of the week. Contrary to this belief, they discover that the expected returns on common stocks and treasury bills are not constant across the days of the week. Most notably, they find that Monday's returns have unusually low or even negative mean. Additionally, they report that stocks tend to rise from Tuesday to Friday and that the gains are largest on Friday and Tuesday. However, regardless of investigating several explanations, they could not explain these phenomena. Smirlock and Starcks (1986) examine day-of-the-week effects using hourly values of the Dow Jones Industrial Average (DJIA) for the 1963-1983 period. They find that weekend effect has shifted from characterizing active trading on Mondays to characterizing the non-trading weekends. Over the early part of their sample period, negative returns characterize each hour of trading on Monday, while the return from Friday close to Monday open is positive. In the most recent sub-period, Monday average hourly returns after noon are all positive and the weekend effect is due to negative average returns from Friday close to Monday open. Harris (1986) also provides the same evidence. He finds that for large firms, negative Monday close-to-close returns accrue between the Friday close and the Monday open. However, for smaller firms the weekend effect accrues primarily during the Monday trading day, which might be explained by poorer liquidity.

However, the most recent studies have found that the weekend effect has disappeared, at least in equity markets, sometime during the last two decades. For instance, Kamara (1997) proves the disappearance and shows that it happened the soonest for the largest firms. Chen and Singal (2003) argue that the introduction of options on a firm’s stock is what led to the elimination of the weekend effect in a specific firm. This is also consistent with Kamara (1997), since options tended to be introduced first for large capitalization firms. However, Chen and Singal come to another conclusion. They argue that the effect actually has just changed the address. They base their story on the original implications of Fields (1931) that risk-averse investors might want to close out their positions on Friday afternoon and open them again on Monday morning. Chen and Singal modify this intuition by suggesting that it is the short sellers that are most interested in closing positions before the weekend. They support their hypothesis with the observation that the weekend effect was most pronounced in stocks with high levels of short interest and on the finding that the weekend effect disappeared only for those stocks on which options are traded.

Several studies report a U-shaped pattern in intraday returns, volatility and volume of stock markets. Jain and Joh (1988) examine hourly common stock trading volume and returns on the New York Stock Exchange. Their results show that the average trading volumes across six trading hours of the day differ significantly. Average volume is the highest during the first hour, declines monotonically until the fourth hour, but increases again on the fifth and the sixth hours. Additionally, they find significant day-of-the-week effects in the data set. Also, stock returns differ across trading hours of the day. On average, largest stock returns occur during the first (except on Monday) and the last trading hours. The lowest average return is earned in the fifth hour of the day. Many of the details of the day of the week and the hour of the day effects documented by earlier researchers are generalized over a longer period examined here. In particular, average stock returns are significantly negative only during the first hour of Monday. Harris (1986) confirms fundamentally the same results. For all firms, significant weekday differences in intraday returns accrue during the first 45 minutes after the market opens. Statistically speaking, the most notable is difference in mean returns is an increase in prices on the last trade of the day. On Monday mornings prices drop, while on the other weekday mornings, they rise. However, Harris states that otherwise the pattern of intraday returns is similar on all weekdays.

Admati and Pfleiderer (1988) examine reasons and theory behind the financial market patterns. The paper explains many patterns, but a significant amount of trading patterns remains unexplained. They present a theory of trading patterns in markets based on models they created. Their main idea was that in equilibrium discretionary liquidity trading is typically concentrated. And if discretionary liquidity traders can allocate their trades across different periods, then in equilibrium their trading is relatively more concentrated in periods closer to the realization of their demands. However, they state that the actual timing and shape of trading patterns in financial markets are determined by a number of factors and parameters that are exogenous to the model, e.g. the rate of arrival of public information. Their empirical observations suggest that the daily patterns in trading volume and returns are quite profound. In particular, there is heavier trading at the beginning and at the end of the trading day, than there is in the middle of the day, and the returns and price changes are more variable. Combining Admati's and Pfleider's results and some earlier hypotheses might explain the high volume of trading at the open and at the close. The key thing is that before the open and after the close trading is almost impossible. Thus, nondiscretionary liquidity traders might trade more actively at the open and at the close, which might propel also discretionary liquidity traders to trade. Additionally, Admati and Pfleider note that settlement rules in many market places might drive the high volume at the close. More particularly, they suggest that since the delivery of the shares depends on the day in which the transaction takes place, liquidity traders must have fulfilled the quantity required by the end of the trading day. Additionally, some traders might want to close the positions during the same trading day to avoid e.g. margin calls.

2.2.2 Option market patterns

Option patterns tend to differ slightly from stock patterns, even though the underlying stock(s) acted similarly as the other stocks. Chan et al. (1993) find that stocks lead options. They find no evidence that options, even deep out-of-the-money options, lead stocks. They also show that their results can be explained as spurious leads induced by infrequent trading of options. The authors show that the stock lead disappears when the average of the bid and ask prices is used instead of transaction prices. Hence, they find no evidence of arbitrage opportunities associated with the stock lead.

Unlike the U-shaped patterns in trading volume, documented in various stock pattern studies, Stephan and Whaley (1990) report a distinctly different intraday pattern for call options traded on the Chicago Board Options Exchange (CBOE). They report that trading volume is lowest at the open and rises to its highest level by approximately 45 minutes into the trading day. A decline in trading volume is then observed, but less pronounced than that documented for the underlying market. An increase in option trading volume before the close of the underlying market is then observed. This is followed by a sharp fall during the close of options trading. Some studies also report the peak after the opening to occur a little bit earlier. E.g. Mayhew et al. (1995) show that trading frequency peaks after the first 30 minutes of trading, whilst Chan et al. (1995) report that trading volume peaks as early as 5 minutes after the market opens on the CBOE. These differences between stock market and option market opening returns are explained mainly with structural attributes. For example, CBOE does not use sequential call opening procedure and the dealer structure is different than what in New York Stock Exchange (NYSE). Aggarwal and Gruca (1993) examine the trading behavior when option market trading hours continue after the close of the underlying market. They find that the rate of option trading on the CBOE rapidly increases in the 10 minutes following the end trading in the underlying market, but then decreases in the last 5 minutes. The observed intraday patterns in trading volume do not solely occur in the USA. Berkman (1992) confirms a similar pattern for equity call options traded on the former European Options Exchange (EOE). Option trading volume in EOE is low during the first 30 minutes, but it peaks for the next two hours of trading and then falls off before increasing to a higher level for the last two hours of trading.

Price volatility of options exhibit a familiar U-shaped pattern found in the underlying market across the trading day. Sheikh and Ronn (1994) document these intraday variations in volatility for CBOE options across the trading day. They also note that, if the arrival of private information about the underlying asset is identical across the stock and options markets, then there should be similarities in the behavior of stock returns and IV returns. However, they only examined returns over, not during, the first hour of trading. Hence, they cannot exactly detect the slight delay in patterns at the start of the trading. Additionally, Chan et al. (1995) show that standardized mid-quote return volatility follows a U-shaped pattern, where returns for CBOE options are more volatile at the open relative to the close of trading in the underlying market. A decline in volatility during the last 10 minutes of CBOE trading (i.e. when the underlying market is closed) is then observed. This result is theoretically consistent with the explanation that the absence of a price for the underlying security will lead to a decline in options' trading. Additionally, Chan et al. (1995) observe, unlike the U-shaped pattern in NYSE, an L-shaped pattern for bid-ask spread of CBOE options, where spreads are wider at the opening period of the trading day than near the close. Additionally, Gwilym et al. (1998) confirm these L-shaped patterns in spreads for stock index options traded on the London International Financial Futures and Options Exchange (LIFFE), an open outcry market with competing market makers. By contrast, Berkman (1992) finds that the bid-ask spreads on the EOE during the trading day are high at the open, decline as trading progresses and then widen in the last two hours of trading. Berkman suggests that the opening of the American stock and option markets increases uncertainty in options traded on the EOE.

2.3 Volatility trading

2.3.1 Instruments

Until the latest years, straddle positions have been the most common way to trade volatility. Bollen and Whaley (2004) state that a straddle is the most effective way to trade options if one has a view of change in the volatility. A trader can construct the straddle to both directions depending on the assumed direction of the change in volatility. Profits/losses can be argued with the fact that higher volatility means higher option prices (Black and Scholes, 1973).

A long straddle is constructed by buying both call and put option with the same underlying asset, strike and maturity date. Thus, the trader is positioned in a way that if volatility increases (the underlying asset value changes more than the markets have expected), the trader will benefit. A short straddle is a similar position, but it bets on decreasing volatility. In short straddle a trader sells a put and call option with same strike and maturity. If volatility decreases trader will profit, since lower volatility equals lower option prices. Nonetheless, short straddle is a highly risky position since the losses are not limited at all. Short straddle can be hedged by restructuring the position as a so called long iron butterfly position. In long iron butterfly, besides normal short straddle, the trader also buys out-of-the-money call and put options. Typically, the distance between each strike prices are equal in this strategy. Naturally, this hedging is done at the expense of lower profits from original straddle position.

Most of the relevant studies (see, e.g. Ahoniemi, 2009; Noh et al., 1994; Harvey and Whaley, 1992; Brooks and Oozer. 2002), which model and forecast implied volatility and run through a trading simulation, use straddles. However, at this time volatility futures were newly established and thus they were not used. Konstantinidi et al (2007) use VIX futures in their trading simulations for VIX estimates. Using straddles is the best way to trade volatility with options, but volatility futures are more effective way to trade volatility. Besides implied volatility (*vega*), options prices are affected by time to maturity (*theta*), risk-free interest rate (*rho*) and price of underlying (delta). For volatility trading it is essential to create trading strategy so that exposure to other variables is minimized. This delta, rho and theta neutrality is achievable, but it is often very costly. In this case theta and rho are not that important because they both affect also futures prices and the effect is anyway relatively small. When straddle is trading approximately at-the-money, the *delta*[4] of the position is close to zero, i.e. delta is neutral. Then again, if the price of the underlying asset moves substantially in either direction (or the straddle is constructed so that the strike price is far away from the spot price), the straddle essentially becomes a short or a long position of the underlying asset. Hence, to retain the delta-neutrality, position should be dynamically hedged constantly. This (buying and selling options) is naturally very costly. Volatility futures on the other hand are more sensible, because the exposure is (almost purely) to only volatility. Ahoniemi (2009) provides empirical evidence of straddles failing to be volatility trades. In her sample, if a trader would have guessed direction of volatility right each time, he still would have lost in 493 days out of 1258 days (39.2%).

[4] Delta measures the rate of change of option value with respect to changes in the underlying asset´s price.

2.3.2 Market inefficiency opportunities

Another theme for research is the opportunities provided by short comings of option pricing models. Poon and Pope (2000) examine an interesting volatility trading opportunity. They state that if returns on two assets share common volatility components, the prices of options on the assets should be interdependent and the implied volatility spread should mean revert. In their trading simulation S&P 100 call options (OEX) are bought and S&P 500 call options (SPX) simultaneously are sold (or vice versa). Their vega-delta-neutral strategies generate significant profits, even after transaction costs are taken into account. Ederington and Guan (2002) examine if volatility smile can provide economic profits. They buy options at the bottom of Black-Scholes smile and sell options at the top. They find that such a strategy yields substantial pre-transaction-cost profits. Moreover, these profits vary in line with the Black-Scholes model's predictions, while they should not if the true volatility smile is flat. Their calculations suggest that roughly half of the observed smile in the stock index options market is due to a smile in the true implied volatilities, with the remainder apparently due to a difference between the Black-Scholes implied volatilities, and the true implied volatilities should not be profitable even on a pre-transaction-cost basis.

3. Hypotheses

The study tests two aspects of intraday implied volatility. Firstly, I examine weekly and daily patterns of implied volatility. Secondly, I try to model intra-day implied volatility changes. Additionally, I examine the statistical significance of economic and financial variables and time-related dummy variables in the models. The dummy variables will also shed light on the implied volatility patterns. Based on these two approaches I have formed underlying hypotheses for the empirical section.

> **Hypothesis 1.1:** *Day-of-the-week effects exist and thus implied volatility is not equal each trading day.*

Several studies have found significant day-of-the-week effects and intraday patterns in financial markets. Implied volatility, which is the pricing instrument of options, should follow closely return and volume patterns of options. Additionally, since I am studying IV of EURO STOXX 50, the IV patterns should be somewhat similar to what previous studies have found to exist in equity markets. Actually, while the negative correlation between equity IV and equity returns have been widely recognized, a relationship between option volumes and IV have not been detect. E.g. Kawaller et al. (1994) find a strong link between trading volume and historical volatility but no stable relationship between volume and implied volatility. Thus, one assumption is that implied volatility patterns might follow more closely equity returns than option trading volumes. On the other hand, IV might form its own patterns as well. Gibbons and Hess (1981) find that Monday's stock returns have unusually low or even negative mean. Additionally, they reported that stocks tend to rise Tuesday through Friday and that the gains are largest on Friday and Tuesday. Implied volatility should face different kind of weekend effect than other markets. Since the early theories, return-generating process of stock prices has found to respond instantaneously to information entering the marketplace. Since the release of any unexpected information tends to be random and continuous through time, stock price changes should follow a random walk in continuous calendar time. Therefore, the mean and variance of the returns calculated from Friday's close to Monday's close should be about three times those of the other trading days of the week. Thus, investors might want to buy options on Friday to hedge their positions over a weekend. On the other hand, formulas and models used to calculate IV are not flexible with the time, i.e. through a trading day the time to maturity remains constant. Hence, ceteris paribus the option price at the close will be less than the option price at the open because options are then closer to the expiration of the contract. Hence, at the end of the day, when the option prices are lower, the calculation of implied volatility will be inaccurately lower as well. This effect is accentuated on Fridays, just before two days of trading inactivity over the weekend. Additionally, as the correlation between equity market and implied volatility is on average negative, the weekend effect should reflect to IV oppositely. Thus, IV should decrease on Fridays. While the stock markets tend to rise on Friday, the IV should actually drop on Friday. Additionally, most recent studies have found that the weekend effect has disappeared (Kamara, 1997), or at least changed addresses (Chen and Singal, 2003).

Nevertheless, implied volatility has been found to possess weekend effect. Many studies [e.g. Harvey & Whaley 1992, Brooks and Oozer 2002 and Ahoniemi (2009)] find that implied volatility tends to rise on Mondays, fall slightly on Tuesdays, Wednesdays and Thursdays and then drop more drastically on Fridays. These results have also been found to be helpful in modeling interday implied volatility. Additionally, the earlier IV literature providing evidence on weekday seasonality has been conducted with close-to-close observations. Thus, the intraday dataset can provide insight on the question that whether the weekend effect actually occurs during the weekend, from Friday close to Monday open, or does the effect still last during the Monday trading. Thus, I am testing the day-of-the-week effects of implied volatility and more precisely whether the effects actually occur during the trading days.

Hypothesis 1.2: *Intraday patterns exist and thus implied volatility is not equal each trading hour*

Secondly, earlier studies report significant intraday patterns in equity and option markets [e.g. Jain and Joh (1988) and Harris (1986) in equity markets and Stephan and Whaley (1990), Aggarwal and Gruca (1993), Mayhew et al. (1995) and Chan et al. (1995) in option markets]. Again, implied volatility should follow these patterns. As the equity markets seem to have a U-shaped pattern, option markets’ pattern is often L-shaped. Moreover, the increase in trading volumes occurs later in the trading in option markets than in equity markets. In equity markets, trading volume peaks directly in the open, while in option markets volume peaks somewhere during the first hour of trading. Low trading volume should also affect in implied volatility. When the trading volume in options is low, IV should be pretty stable at the point. Then the variance in IV should increase after the volume picks up. Even though the volume picks up the IV should decrease as the stock markets tend to go up in the mornings. Then implied volatility should increase during the middle of the day as the stock markets on average decline at that time. An increase in option trading volume before the close of the underlying market is then observed. This is followed by a sharp fall during the close of options trading. Equity returns on the other hand experience increase at the end of each trading day. Thus, it is expected that IV declines at the end of the day. Moreover, the decline should be more drastic 15-30 minutes before the close, than right before the close. Also, these patterns vary between trading days and the patterns most likely are not same for Mondays and Fridays. Hence, I study whether patterns within in the trading days exist and are they similar in all weekdays?

Hypothesis 2.1: *Implied volatility of EURO STOXX 50 can be modeled and forecasted with 1-minute and 10-minute interval in observations*

Majority of the related studies have found that implied volatility can be modeled at least on statistical level. I test this with a new set of data using similar methodology as used in these studies. I use two intraday datasets of VSTOXX. American colleague of VSTOXX, the VIX index, has been widely used in interday modeling of IV. Furthermore, only Konstantinidi et al. (2007) have examined IV of EURO STOXX 50 using data from VSTOXX, but the data was interdaily. The intraday implied volatility should also be modelable. After all, the data should be more autocorrelated when the observations are closer to each other. Autocorrelation is essential for ARMA models. Additionally, intraday data sets have been only used in GARCH modeling of historic volatility. Andersen and Bollerslev (1998) stated that 5-minute interval was the highest and the best frequency they modeled currency exchange rates. Thus I will now test both 1-minute and 10-minute intervals to find out, if the higher frequency provides any additional information.

Hypothesis 2.2: *Previous (T-1) observations of the economic/financial variables and the dummy variables for intraday patterns contain information on implied volatility at intraday level*

Regarding the modeling, I also examine whether the economic and financial variables can improve accuracy of the models. Overall, earlier literature has not found these variables to be useful. Konstantinidi et al. (2007) tested for wide range of variables with poor results. Additionally, Ahoniemi (2009) as well tested for many variables, but found only first lags of the underlying S&P500 changes to be significant as well as weekday dummies. Now, since this study uses an intraday data set this might not be the case. Andersen and Bollerslev (1998) find that intraday returns provide much more accurate measures of realized volatility than daily returns as well as providing more accurate forecasts. Although high-frequency returns are highly informative about future volatility, they find that implied volatilities are more informative throughout their sample. That is, the information might spread to IV from equity and currency markets with a time lag, which however is less than one day. Hence, I use the observations of several economic/financial variables from the latest minute (T-1) to model the VSTOXX at the next minute (T).

Additionally, I introduce new set of dummy variables: the hour dummies. Since weekday dummies have been found to be useful in earlier literature for forecasting IV, it could be the same case with hours as well. As mentioned, earlier studies have found significant intraday patterns in equity and option markets. Thus, e.g. the dummy for the closing “hour”, CET 18:00-18:30, should be significant. Furthermore, for example during the time when economic data is released in the US, the market changes might be more rapid. A quick view on the hourly averages of VSTOXX shows that this in fact might be the case. During hours when majority of critical economic data is released (during CET 14:00) and when stock markets open in the US (during CET 15:00), the average value is higher than e.g. during the morning hours. I also test the weekday dummies for this intraday dataset.

4. Data and methodology

In this section I introduce the data and methodology used in this study. I firstly present the VSTOXX Index, its underlying EURO STOXX 50 Index and VSTOXX futures, and how the futures are traded in the EUREX exchange. Secondly, I will describe all the data I used to model VSTOXX, including the VSTOXX data and data for economic/financial explanatory variables. Thirdly, I will shortly introduce basic theory and previous literature on time series econometric methods used in this thesis. And finally, in the fourth part, I introduce more precisely the methodology used in modeling and forecasting intraday observations of VSTOXX.

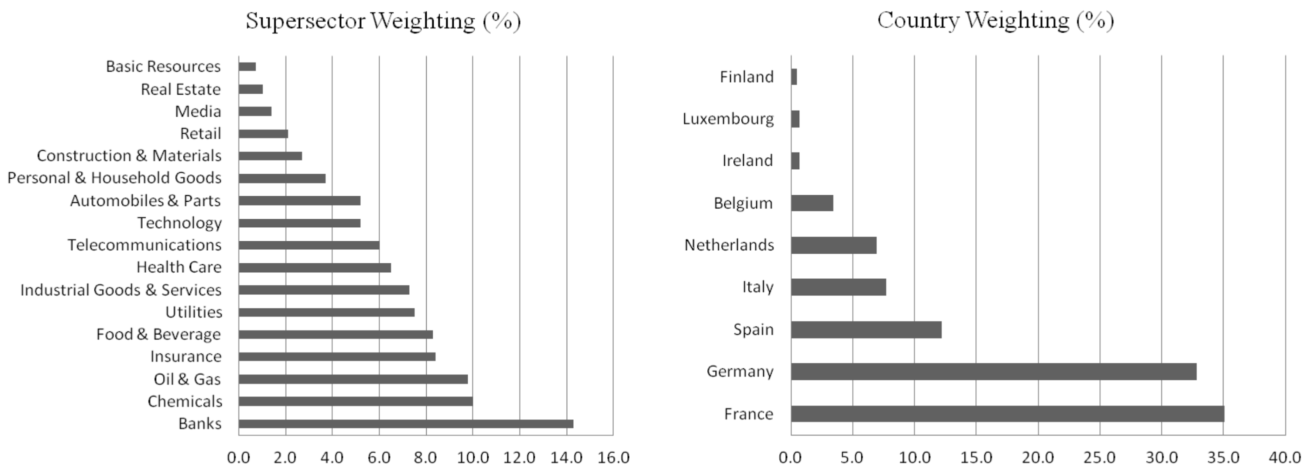
4.1 EURO STOXX 50 and its implied volatility

4.1.1 EURO STOXX 50 index

EURO STOXX 50 is the leading blue chip index in Europe. It is calculated by STOXX Limited, which is an index provider owned by Deutsche Börse and SIX Group. The index consists of 50 supersector companies' stocks from 12 Eurozone countries. The stocks are weighted as free float market capitalization, but are subject to 10% weighting cap. The weights are reviewed annually in September. It captures currently approximately 62% of the free float market capitalization of EURO STOXX Total Market Index, which in turn covers approximately 95% of the free float market capitalization of the represented countries. There are companies from 9 countries in the index. The biggest sector in the index is Banks, which has a weighting of 14.3% as of 28th of September 2012. Supersector weightings and country weightings of the index are presented in Figure 1 on the next page.

Figure 1 – Countries and sectors of EURO STOXX 50 companies

The figure describes the country weightings and the supersector weightings of EURO STOXX 50 index on 28th of September, 2012. The EURO STOXX 50 index is a blue chip capitalization-weighted index consisting of 50 supersector leaders of the Eurozone.



Source: EURO STOXX 50 index factsheet.

EURO STOXX 50 is widely followed by academics and especially practioners. E.g. its futures are clearly the most traded index future contracts in Europe. Thus, EURO STOXX 50 has leading role as a European benchmark stock index. Additionally, there is a significant amount of exchange-traded-funds (ETFs) following EURO STOXX 50 index[5].

Table 1 – Turnover volume of index futures January - June 2012 in Europe

The table shows the turnover volumes of European index futures in the first half of 2012. The turnover volume of EURO STOXX 50 is higher than the turnover volume of all the rest most traded index futures.

#	Exchange	Indice	Turnover Volume
1	EUREX	EURO STOXX 50	175 401 268
2	EUREX	DAX	20 835 534
3	Liffe NYSE EURONEXT	CAC 40	20 212 097
4	Liffe NYSE EURONEXT	FTSE 100	17 764 333
5	OMX	OMXS 30	17 264 864
6	Liffe NYSE EURONEXT	AEX	5 596 960
7	EUREX	EURO STOXX BANKS	5 221 985
8	WSE	WIG 20	5 058 805
9	EUREX	SMI	4 788 998
10	ITALY	FTSE MIB	2 954 951

SOURCE: Eurex

5 Source EURO STOXX 50 Index Factsheet

4.1.2 The VSTOXX index

The VSTOXX index is based on implied volatility of EURO STOXX 50. To be more specific, it is based on real-time options prices across all options of a given time to expiration. The main index VSTOXX is designed as a rolling index at a fixed 30 days to expiry. The sub-indexes represent the eight expiry months with a maximum of 2 years. To tackle the imperfections of B-S model (or other similar models), model-free methods of recovering implied volatilities directly from option price quotes, have emerged in recent years. Thus, encouraged by the VIX of Chicago Board of Exchange that has been calculated with a model-free methodology since September of 2003, the VSTOXX also switched to similar methodology. The greatest distinction between the model-free method and the volatility derived from the option pricing models is that the first mentioned relies on much less restrictive assumptions. Although, assumptions of frictionless markets with no arbitrage opportunities and continuous return distribution of the underlying asset are still present in the model-free measures, the assumptions of the return generation process are not made.

The VSTOXX is calculated by using the two nearest expiration months of EURO STOXX 50 options. A rollover to the next expiration occurs eight calendar days prior to the expiry of the nearby option. The value of the index is derived from the prices of out-of-the-money and at-the-money puts and calls. The closer the option's strike price to the at-the-money value, the higher the weight its price receives in the calculation. VSTOXX is calculated directly from option prices, rather than solving it out of an option-pricing formula, which considerably relieves the problems of measurement errors and model misspecification that arise when option-pricing models are employed.

During the calculation hours for the VSTOXX (8:50 to 17:30 CET), the following data is used via snapshots every five seconds:

- EURO STOXX 50 Index
- OESX – Best bid and best ask of all EURO STOXX 50 options
- EONIA (Euro Over-Night Index Average) – overnight interest rate
- EURIBOR (Euro Interbank Offered Rates) – money market reference rates for 1 to 12 months (calculated once a day, 11:00 CET, by the European Banking Federation)

- REX – Yield of the 2-year REX, indicator for German government bonds, as the longer-term interest rate (also calculated once a day using exchange-traded prices from the Frankfurt stock exchange by Deutsche Börse Group)

The index is calculated with following formula:

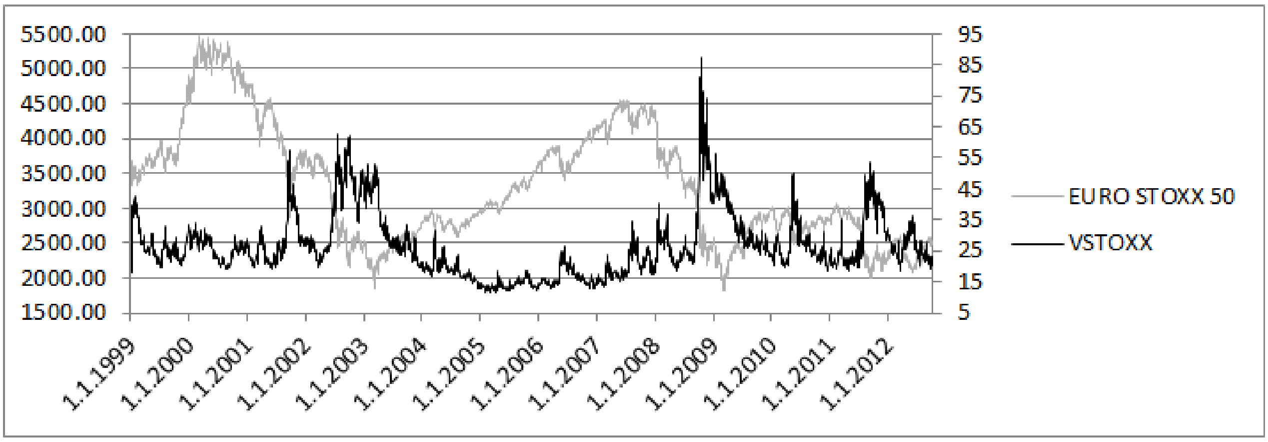
$$\sigma = \sqrt{\frac{2}{\tau}\left[\sum_{i=1}^{N-1}\frac{\Delta X_i}{X_i^2}e^{r\tau}Q(X,\tau) + \frac{X_2+X_1}{2X_i^2}e^{r\tau}Q(X,\tau) + \frac{X_N+X_{N-1}}{2X_N^2}e^{r\tau}Q(X,\tau)\right] - \frac{1}{\tau}\left[\frac{F}{X_0}-1\right]^2} \tag{4}$$

,where F is the forward index level derived from option prices; τ is time to expiry of the i^{th} OESX; X_i is the strike price of the i^{th} out-of-money OESX; ΔX_i is the interval between strike prices; X_0 is the first strike below F and $Q(X,\tau)$ is the midpoint of the bid-ask spread for each option with strike X_i. Thus, the VSTOXX does not measure implied volatilities of ATM options, but the implied variance across all options of given time to expiry. Besides, to avoid the shortcomings of the option pricing models, the calculation method aims at making pure volatility tradable. Hence, the index should be trackable by a portfolio which is delta-neutral, and only reacts to changes in volatility.

The value of VSTOXX has historically been somewhat higher than the most followed IV index the VIX, which has S&P 500 index as underlying (Figure 2). The average value of VSTOXX, from the beginning at January of 1999 to October of 2012, has been 26.35 %. At the same period the average value of VIX has been 22.22%. As mentioned, European banks have a very large weighting in the EURO STOXX 50, which have caused turmoil for the index during the latest financial crises.

Figure 2 – Values of VSTOXX and EURO STOXX 50

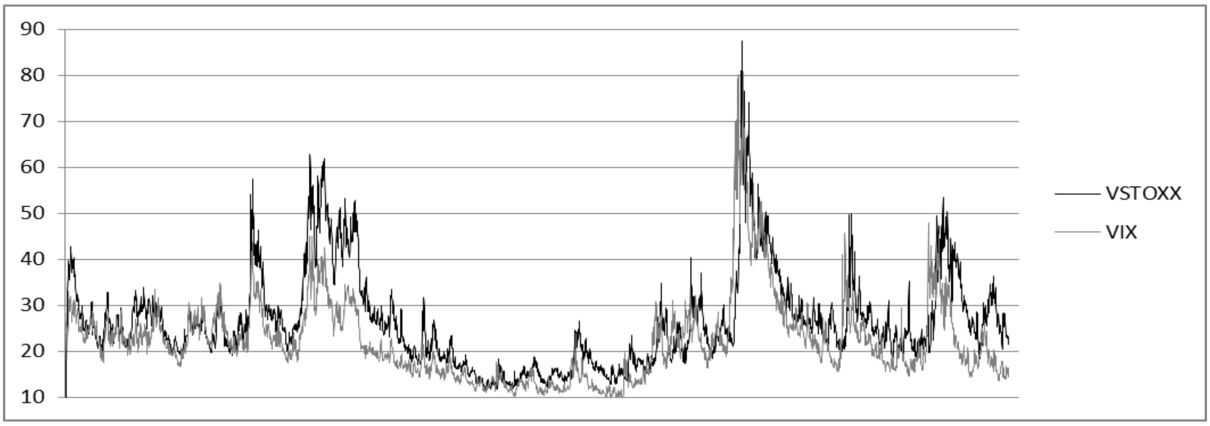
The chart clearly shows how the VSTOXX and its underlying EURO STROXX 50 index generally tends to move to opposite directions and that stable VIX (around 15-25%) usually means bull market.



The VIX Index, which is the most followed IV index in the world, is often called as the "investor fear gauge". Since the VIX is constructed from the implied volatilities of S&P 500 options – the most followed stock market index in the world – it is fair to define it as a measure of expected stock market risk. The definition has been very incisive: the VIX has acted reliably as a fear gauge since the beginning of the index calculation. High levels of VIX are coincident with high degrees of market turmoil (Whaley, 1993B). Panerjee et al. (2007) found that VIX variables significantly affect returns for most portfolios, with the relationship stronger for high-beta portfolios. In similar way, VSTOXX has obtained the same nick name, which is not that commonly used though as with VIX. However, VSTOXX can be used to value stock market risk in EURO STOXX 50 and thus the risk in the whole Eurozone. Simon (2003) suggested that demand for put options increases after a drop because investors are more willing to buy insurance for their portfolios. The increased demand naturally raises the prices of options and thus implied volatility rises. He also added that when market rises, options with higher strike prices become eventually at-the-money options. Since as well-documented volatility smile suggests, options with higher strike have smaller IV. Thus, IV decreases, even though the IV of the certain option, that is then an ITM option, has not changed.

Figure 3 – Historical values of VSTOXX and VIX

This table describes the historical values of VIX and VSTOXX. On average, VSTOXX has had a higher value indicating that volatility, or risk, in EURO STOXX 50 is higher than volatility in S&P 500.

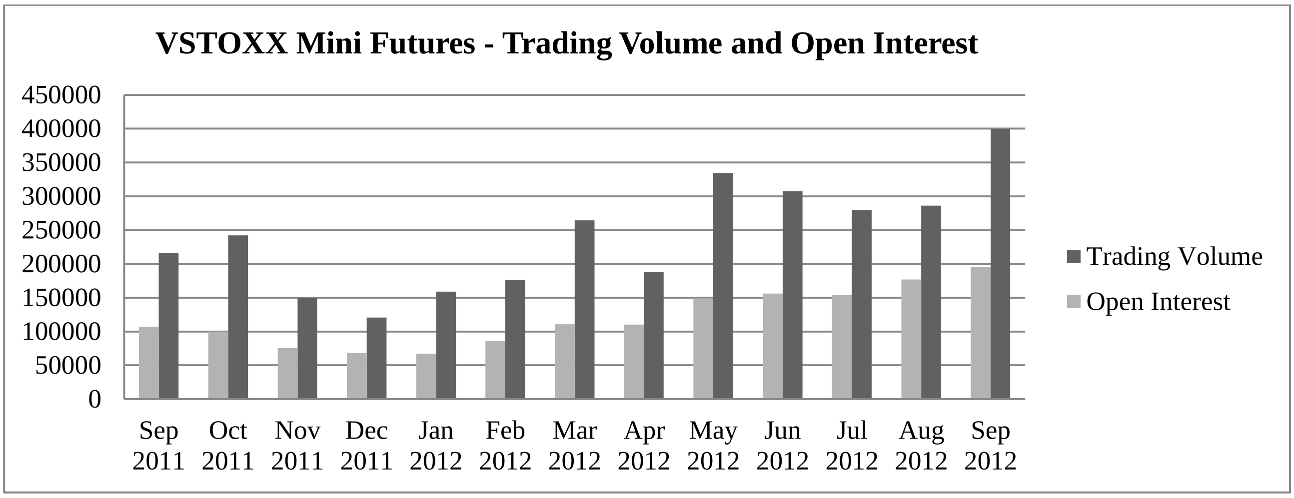


In 2005, Eurex introduced volatility index futures as a new asset class. In 2008, driven by customer demand, Eurex changed its VSTOXX futures into VSTOXX Mini Futures. The only difference between the Mini Futures and former normal futures is the contract size, which was changed from EUR 1000 to EUR 100. CBOE Futures Exchange has been offering VIX futures since 2004. Prior to that, volatility was traded only with over-the-counter derivatives and by constructing straddle positions with options. The contract value of VSTOXX futures, currently called VSTOXX mini futures, is EUR 100 per index point of the underlying. Hence, if VSTOXX is at 25.00, value of one contract is EUR 2500. Price quotation is in points with two decimal places, while minimum price change is 0.05 points, equivalent to a value of EUR 5. The futures are settled with cash on the final settlement day, which is also the last trading day. This is usually the Wednesday prior to the second last Friday of the respective maturity month, if this is an exchange day. Otherwise, the final settlement day is the exchange day immediately preceding that day.

Volume of traded contracts of VSTOXX futures has lately picked up significantly. In September 2012, the trading volume recorded a new high. Almost 400,000 contracts were traded during September and the same development has continued in October as well. The daily volume is nowadays about 20,000 contracts, while the daily average during 2010 was only 1686 traded contracts. Majority of the volume is actual screen volume and only on average some 20% of the trades are executed over-the-counter. Open interest has also been high: during the whole October of 2012 number of open positions has remained at over 200,000 contracts. Additionally, volume of VSTOXX options has increased significantly. The average daily trading volume has more than doubled from 2154 contracts in 2011, as it has been 4407 contracts from January to September 2012. Figure 3 shows the monthly trading volumes and open interest of VSTOXX mini futures:

Figure 4 – Trading volume and open interest from September 2011 to September 2012

The figure demonstrates the increased trading volume and open interest in VSTOXX mini futures. Volume has increased significantly which in other words means that the liquidity has improved in the VSTOXX futures market. SOURCE: Eurex Monthly Statistics September 2012.



4.2 Data analysis

Data for VSTOXX, VSTOXX futures and various financial and macroeconomic indicators was obtained from Bloomberg. I use two samples: one with 1-minute observation interval and another one with 10-minute interval. The sample period for both samples is from January 11th, 2012 to November 31st, 2012. The subset from January 11th to 31st of August will be used for the in-sample evaluation and the remaining data will be used for out-of-sample evaluation. Public holidays that fall on weekdays were excluded from the dataset. Number of observations in in-sample period of 1-minute data set is 81,539 and in 1-minute set 8241. In full sample the number of observations is 111,742 observations in 1-minute dataset, and in 10-minute data 11,237 observations respectively.

Additionally, I use several explanatory variables to improve modeling, which are summarized in Table 2. Majority of earlier literature has used similar approach for modeling IV. Ahoniemi (2009) tested for several variables, but found only two weekday dummies (for Monday and Friday) and previous returns of underlying S&P500 to be statistically significant. Thus, when speaking of VSTOXX, it is fair to expect the lagged returns of underlying EURO STOXX 50 to be significant. Furthermore, Konstantinidi et al. found that all of the economic variables that they tested for VSTOXX were insignificant. Additionally, altogether only 4 variables were found to be significant when regressed on the 7 volatility indices, which they were studying. DAX and STOXX EUROPE 600 stock indices are used to test for spillover effects between indices, which might also lead to volatility spillover that has been documented across different markets. Additionally, STOXX EUROPE 600 might give information from wider range of stocks. After all, EURO STOXX 50 contains a lot of banks, which has caused the blue chip index to decline much more than the STOXX EUROPE 600 during the financial turmoil of 2012. EUR/USD and EUR/CHF exchange rates and gold price are often used as safe havens during turmoil in other asset classes. Since the VSTOXX is also used as a safe haven for Eurozone stocks, it is justifiable to test if these indicators can help to model implied volatility.

The nature of this study sets certain limitations. Many of the indicators used in previous studies cannot be used, because there is no data available with 1 minute or 10 minute intervals for many indicators. E.g. Euribor interest rates are calculated only once day and thus intraday data is not available. However, these variables have not been statistically significant in majority of related studies[6].

[6] E.g. Ahoniemi (2009) and Konstatinidi et al. (2007) found 1-month Euribor or U.S interbank interest rates and many other financial and economic variables to be statistically insignificant

Table 2 – Summary of variables tested

The table describes the 8 variables to be tested in the study, as well as whether previous studies have used similar variables for implied volatility modeling.

Variable	Explanation	Previous studies
DAX	A blue chip stock market index consisting of the 30 major German companies.	No
STOXX EUROPE 600	A stock market index containing 600 European companies.	No
EUR/USD	Euro to US dollar spot exchange rate. Many changes in the world's economy and financial markets reflect to this leading currency rate.	Yes
EUR/CHF	Euro to Swiss franc spot exchange rate. Especially during the financial crisis in Southern Euro countries, Swiss franc has been used widely as a safe haven.	No
Gold	Spot price for Gold forwards from London Metal Exchange. Gold has been used as safe haven for almost all asset classes.	Yes
EURO STOXX 50	EURO STOXX 50 index, for more information on the index see section 4.1.1.	Yes
Weekday dummies	Weekday dummy for all the weekdays. The dummy gets value 1, when is the day indicated by dummy, otherwise zero.	Yes
Hour dummies	Hour dummy for all the trading hours (9:00 CET to 17:00 CET). The dummy gets value 1, when is the hour indicated by dummy, otherwise zero.	No

Appendices 1 and 2 describe all the series and all the data sets. Mean values and standard deviations are very similar in both datasets. During the in-sample-period, VSTOXX reached minimum value of 17.3% and maximum value of 38.3%. The average value was 26.45 % during in-sample period and 25.22 during the combined in-sample and out-of-sample period.

With 1-minute observation intervals, average change in the full period was -0.00009% and the standard deviation of the changes 0.05%. Respectively with 10-minute data, average change was -0.009% and standard deviation of changes 0.19%.

Logged datasets were used to avoid negative volatility. Additionally, Simon (2003) argued that using logs is in-line with positive skewness of IV. As Appendix 2 shows, the data is skewed to right in both data sets. The positive skewness has been reported also in other implied volatility studies. Excess kurtosis is very high in differenced data, as expected. Moreover, Augmented Dickey-Fuller (ADF) tests for unit roots suggest, that first differenced logs are the best choice. The differenced data receives clearly the largest t-values, and the null hypothesis of unit roots can be rejected. For level data the hypothesis could be rejected only on 10% significance level (p-value 0.08). Thus, the peremptory requirement for stationary series is best achieved with the differenced data. Jarque-Bera tests indicate normality of errors in both datasets of VSTOXX in all three forms.

VSTOXX is a very persistent time series and the observations display high auto correlation in both 1-minute and 10-minute series with level and differenced data. Significance is measured with widely-used rule of thumb:

$$if \quad |\rho| > \frac{2}{\sqrt{N}}\text{, then } \rho \text{ is statistically significant, where N = number of observations}$$

Autocorrelations (AC) are presented in Figures 4 and 5 on the next page. Level data display over 95% autocorrelation for all 36 lags. Differenced log data with 10 minutes intervals has significant autocorrelation for first two lags. The more frequent 1-minute data sets displays autocorrelation for several lags. Additionally, the logged first difference datasets display significant partial autocorrelation (PAC). Partial autocorrelations are represented in Figure 6 on the next page as well. In short, significant PACs suggest AR models to suit data and ACs to MA models respectively. Thus, ACs and PACs indicate that the data should fit very well for the ARMA modeling.

Figure 5 – Autocorrelations VSTOXX with 1-minute intervals

Autocorrelations for 36 lags of log VSTOXX and log first differenced VSTOXX with 10-minute intervals

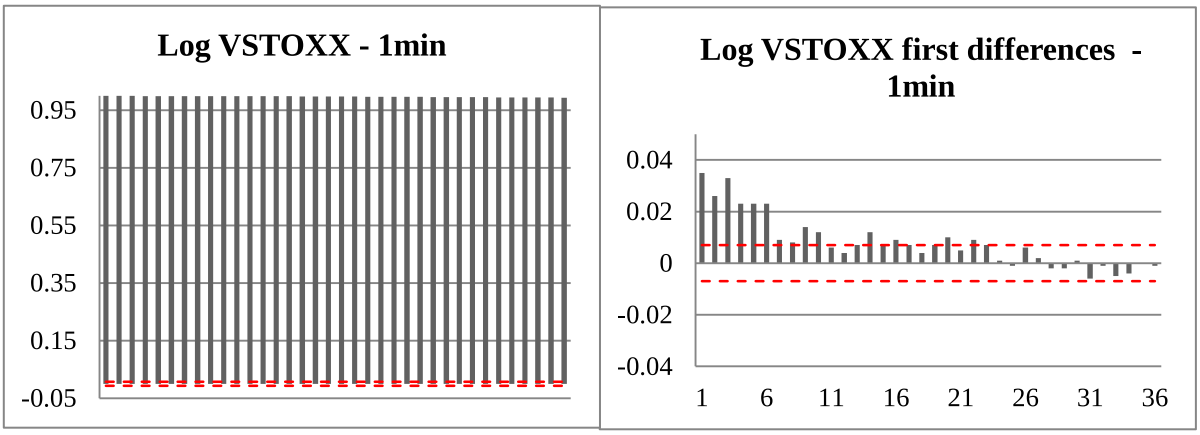


Figure 6 – Autocorrelations VSTOXX with 10- minute intervals

Autocorrelations for 36 lags of log VSTOXX and log first differenced VSTOXX with 10-minute intervals

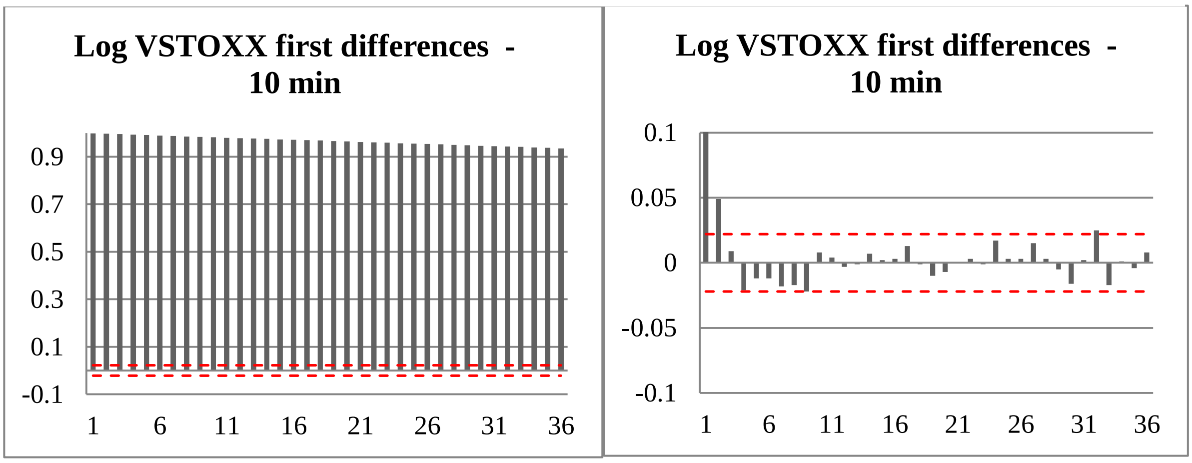
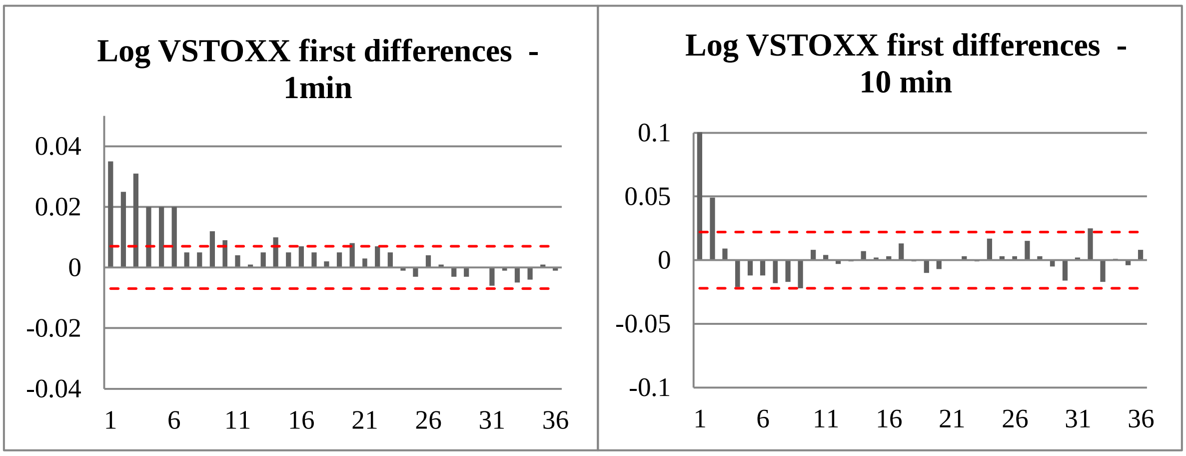


Figure 7 – Partial autocorrelations

Partial autocorrelations of 36 lags log first differenced VSTOXX with 1 minute and 10 minute intervals



Appendix 2 provides also key statistics for VSTOXX futures during the out-of-sample period. The out-of-sample period consists of 30,203 VSTOXX observations. Nevertheless, close, bid and ask quotes for VSTOXX futures are not available for every minute. The futures dataset consists of about 18,000 bid and ask quotes and of only about 6,000 minute close quotes. The idea of obtaining the futures quotes was to carry through trading simulations with the developed models. However, since there is not data available for each minute, the intraday trading simulations cannot be carried through with futures. In order to measure profit generating abilities of models, the trading simulations should be implemented with same intervals which the model is forecasting. Furthermore, there is no sense to implement the simulations with option straddles, because earlier studies (see, e.g. Brooks and Oozer, 2003) have confirmed that they will not provide any economic profits, and because straddle is not nowadays the best strategy to trade implied volatility.

4.3 Time series econometrics

Time series forecasting is the use of a model to forecast future events, based on known past events. Special feature of time series is that the data have a natural temporal ordering, which does not exist in common data. Additionally, time series analysis is also distinct from spatial data analysis, where the observations typically relate to geographical locations. A time series model will generally reflect the fact that observations that are close together in time will be more closely related, than observations further apart in time. In addition, time series models will often make use of the natural one-way ordering of time, so that values for a given period will be expressed as deriving in some way from past values, rather than from future values. There are numerous widely known classes of time series models. Next I shortly introduce theory and previous literature of the time series methodologies used in this study: ARMA and GARCH models.

4.3.1 ARMA family models

Autoregressive Moving Average models are the most general class of models for forecasting time series which are stationary or can be stationarized by transformations such as differencing and logging. Stationarity is a key requirement for a data set to fit for ARMA modeling. It means that there is no trend in the time series; hence its expected value is time-invariant and finite. The variance is also time-invariant and finite. The covariance between observations depends only on the amount of time between the observations s, not on the moment when the observation is made (t). An ARMA model predicts a value in a response time series as a linear combination of its own past values, past errors and current and past values of other time series. The general ARMA model was first described in the thesis of Peter Whittle (1951). The model was then popularized by Box and Jenkins (1976), and thus ARMA models are often referred also as Box-Jenkins models. Box and Jenkins divided ARMA process in to three stages. Firstly, identification of statement to specify the response series and identify candidate ARMA models for it. Secondly, estimation and diagnostic check to specify the ARMA model to fit to the variable specified in the previous stage, and to estimate the parameters of that model. Thirdly, the forecasting of future values of time series.

There are a few ways to choose the best model when estimating the equation. Finding appropriate values of p and q in the ARMA(p,q) model can be facilitated by plotting the PAC functions (partial autocorrelation) for an estimate of p, and likewise using the autocorrelation functions for an estimate of q. Further information can be gleaned by considering the same functions for the residuals of a model fitted with an initial selection of p and q. Some literature sources also recommend using AICs (Akaike Information Criteria) for finding p and q. It is generally considered a good practice to find the smallest values of p and q, which provide an acceptable fit to the data. For a pure AR model the Yule-Walker equations may be used to provide a fit.

Equation to be estimated in basic ARMA (1,1) model is

$$IV_t = \omega + \emptyset_1 IV_{t-1} + \theta_1 \epsilon_{t-1} \tag{5}$$

where $\emptyset_1$ is the autoregressive part and θ_1 is the moving average part and ϵ_t is the error term.

ARIMA (autoregressive integrated moving average) model is a generalization of the ARMA model. The model is usually denoted as ARIMA (p, d, q), where p, d and q are non-negative integers referring to order of autoregressive (AR), integrated (I) and moving average (MA) parts of the model. ARFIMA (autoregressive fractionally integrated moving average) models are time series models that generalize ARIMA (autoregressive integrated moving average) models by allowing non-integer values of the differencing parameter and are useful in modeling time series with long memory. When an ARIMA model also includes other time series as input variables, the model is often called as an ARIMAX model (the X of the acronym).

Equation to be estimated in basic first differenced ARMA, i.e. ARIMA (1,1,1) model is

$$\Delta VSTOXX_t = \omega + \emptyset_1 \Delta VSTOXX_{t-1} + \theta_1 \epsilon_{t-1} \tag{6}$$

Equation to be estimated in an ARIMAX (1,1,1) model is

$$\Delta VIX_t = \omega + \emptyset_1 \Delta VIX_{t-1} + \theta_1 \epsilon_{t-1} + \sum_{t=1}^{r} \emptyset_i X_{i,t-1} + \sum_{k=1}^{5} \gamma\, D_{k,t} + \epsilon_t \tag{7}$$

where Xi´s are the explanatory variables and $D_{k,t}$´s are dummy variables.

ARMA models are used in majority of the previous literature forecasting IV. E.g. Konstantinidi et al. (2007), Ahoniemi (2009), Harvey and Whaley (1992) and Brooks and Oozer (2002) all use ARMA family models in forecasting. All of these studies find ARMA models useful, since all of the models achieve over 50% accuracy in modeling directional change in IV. However, point forecasts do not perform that well. Another common observation in many studies (see, e.g. Ahoniemi, 2009; Aboura, 2003) was that ARMA models performed better in shorter samples[7].

[7] This is also found in studies using other methods, such as GARCH modeling in Blair et al. (2001)

4.3.2 GARCH Model

GARCH is a model for the variance of the error terms. Thus, the model expects that error terms are no longer white noise. GARCH model was introduced by Bollerslev (1986) as an upgrade for ARCH model introduced by Engle (1982). The extension to the ARCH is that GARCH allows for both longer memory and a more flexible lag structure. Since development of these models, they have been widely used in modeling financial volatility. Even if returns of an asset are not predictable, return volatility can still be predictable. The basic idea behind (G)ARCH models is that large shocks are more likely to be followed by large shocks and small shocks by small shocks.

GARCH (1,1) as parameters is

$$\epsilon_t = N(0, h_t^2) \tag{8}$$

$$h_t^2 = \kappa + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{9}$$

To generalize, GARCH has been used in modeling volatility of almost all financial instruments. Hansen and Lunde (2005) provide probably the most thorough analysis on ARCH family models. They compare 330 ARCH-type models in terms of their ability to describe the conditional variance. The models are compared out-of-sample using DM–USD exchange rate data from the years between 1987 and 1993 and IBM return data from 1990 to 2000, where the latter is based on a new data set of realized variance. They find no evidence with the test for superior predictive ability (SPA) and the reality check for data snooping (RC) that a GARCH(1,1) is outperformed by more sophisticated models in their analysis. Whereas the GARCH(1,1) is clearly inferior to models that can accommodate a leverage effect in our analysis of IBM returns.

Blair et al. (2001) have somewhat similar approach as in this study: they forecasted high-frequency data with ARCH models. They compared information content of implied volatilities and high-frequency intraday returns. Data was gathered from 1987 to 1999 on daily returns of the S&P 100 index and the VIX index. The realized volatility was calculated from intraday returns. The extension here of the historic information set to include high-frequency (five-minute) returns shows, that there appears to be only minor incremental information in high-frequency returns. However, this information is almost subsumed by implied volatilities. Out-of-sample comparisons of volatility forecasts show that VIX provides more accurate forecasts than either low-frequency or high-frequency index returns, regardless of the definition of realized volatility and the horizon of the forecasts. Their results for equity volatility confirm the conclusion of Andersen and Bollerslev (1998)[8], that intraday returns provide much more accurate measures of realized volatility than daily returns, as well as providing more accurate forecasts. Although high-frequency returns are highly informative about future volatility, they have found that implied volatilities were more informative throughout their sample period from 1987 to 1999. Noh et al. (1994) is one of few relevant researches to report that their model generated profits in excess of transaction costs. They used a GARCH model for S&P 500 and traded straddles to reach this.

4.4 Methodology

4.4.1 Intraday patterns

Methodology for detecting intradaily and weekly patterns follows closely to Harris (1986). I first compute daily returns of VSTOXX from the dataset to study the daily systematic patterns. I use the intraday dataset, and hence I am able not to only calculate close-to-close returns, but also to include open-to-close, open-to-open and close-to-open returns. Thus, I am able to divide the daily changes for trading and non-trading periods. I run F-tests for equal means to find out whether the mean changes are equal on all weekdays. Furthermore, I run the same F-tests for only Tuesday to Friday and Monday to Thursday. Previous literature has found that on Mondays and Fridays the IV changes are the most drastically different from the rest of the days.

To investigate systematic intraday patterns, I compute mean changes for all five trading days by 15-minute intervals. The 15-minute means are then tested with F-tests to find out whether

[8] Andersen and Bollerslev (1998) suggested that as most of the volatility forecast comparisons rely on some variant of the squared return-volatility regression and even if this might be natural when evaluating the conditional mean, they might be less obvious when evaluating volatility forecasts. Thus, further analysis of this might benefit from the use of high-frequency data.

they are equal on all weekdays and at every interval. Additionally, I run the same F-tests for only Tuesday to Friday and Monday to Thursday. Furthermore, I run F-tests for all weekdays to find out whether changes in IV are same in all intervals during the whole trading day. I will then run the same F-tests for “inner” part of trading day. Thus, I exclude opens and closes and I will investigate, whether during the trading day means of changes are equal. Then I run t-tests for close and open mean changes compared to rest of days mean changes to find out whether they are equal. Naturally, I also compute the variances of returns for all intervals.

Finally, I use hour and weekday dummies to confirm the results. I regress the dummies on logarithmic first differences of the VSTOXX. The dummies are originally used for the model part of this study, but they might give helpful insight on intradaily and weekly patterns also.

4.4.2 Modeling

Autocorrelations and partial autocorrelations indicate that ARMA models should fit very well for the VSTOXX datasets. Additionally, Jarque-Bera, Ljung-Box and ADF tests are examined to find out suitability of ARMA family models for both of the time series.

I model two different samples with 1-minute and 10-minute interval. There are two drivers behind this decision. Firstly, previous literature has noticed that shorter sample sizes for modeling perform better in both ARMA models (see, e.g. Aboura [2003] and Ahoniemi [2009]) and GARCH models (Blair et al. [2001]). It would be impossible to shorten the sample into 1,000 observations, as in Ahoniemi (2009), because it would shorten the sample also to about two days. Secondly, Andersen and Bollerslev (1998) reported that 5-minute interval was the highest and the best frequency they used. However, between 1-minute and 10-minute the differences will be more notable. For all of the time series, I will use logarithmic first differences of series, which is suggested by e.g. Ahoniemi (2009) and Fleming et al. (1995). As discussed in these two studies, both practioners and academics are primarily interested in the changes in volatility. Additionally, for economic variables models I use first lags of the data. Thus, to model IV at time t, log change at time t-1 is used.

Firstly I test the ARMA family models. The following ARIMAX model is the primary equation to be estimated:

$$\Delta VSTOXX_t =$$

$$c + \emptyset_1 \Delta VSTOXX_{t-1} + \theta_1 \epsilon_{t-1} + \sum_{t=1}^{r} \emptyset_i X_{i,t-1} + \sum_{k=1}^{5} \gamma\, D_{k,t} + \sum_{k=1}^{9} \psi H_{k,t} + \epsilon_t \qquad (10)$$

,where $D_{k,t}$ is the weekday dummy variable, $H_{k,t}$ is the hour dummy variable, $X_{i,t-1}$ are the economic variables and ϵ_t is the error term. All the economic/financial variables that are found to be insignificant will be excluded from the modeling. Weekday dummy variable receives value of 1 on day k and zero otherwise, and hour dummy 1 during the hour m and zero otherwise, respectively. $\Delta VSTOXX_{t-1}$ is the first lag of first differenced log return of the VSTOXX index and ϵ_{t-1} is the previous error term.

I also test other ARMA family models: AR, MA and ARMA and ARIMA. Equations to be estimated for these models are presented in part 4.3.1. To rank these models, besides significance of the variables, I use R-squared, sum of squared residuals (SSR), Akaike information criterion (AIC) and Bayesian information criterion (BIC) values. To model the data, I will use statistical program EVIEWS that is generally used for time-series oriented econometric analysis.

One-step-ahead forecasts are calculated for the out-of-sample period (September 3, 2012 to November 26, 2012). Forecasting will be conducted for all models and both samples on recursive basis. This means that after each observation, the previous observation is also included in the model. Hence, the model evolves after each observation. The rational is, that this is the way how the forecasting would probably be conducted in real-life – especially among practioners.

Forecasts are then used to rank models, as done in e.g. Ahoniemi (2009). I use the forecasts and calculate how many times the forecasts were right during the out-of-sample period. The models are forecasting logarithmic changes of VSTOXX. As mentioned earlier, the directional accuracy is actually the most important comparison criteria. Furthermore, the direction of changes is the fundamental goal of the models. The out-of-sample directional accuracy will hence be the final determinator for the best model.

5. Analysis and results

In the following section I provide analysis and results of the empirical studies carried through with the datasets. I first analyze the implied volatility patterns. I study day-of-the week effects and intraday patterns. Secondly, I model the intraday VSTOXX with OLS regression models that include ARMA and economic/financial variables. Proper statistical test results are provided to ensure robustness of the results. Additionally, I will reject or accept the hypotheses presented in Section 3.

5.1 Implied volatility patterns

5.1.1 Day-of-the-week effects

The empirical tests with the dataset confirm day-of-the-week effects in implied volatility. Earlier literature (see, e.g. Brooks and Oozer, 2003) has found that, close-to-close IV rises on Mondays. IV then continues to rise slightly from Tuesdays to Thursdays, but then decreases drastically on Fridays. My empirical results support the close-to-close changes found earlier for Mondays to Wednesdays and Fridays. However, IV seems to decrease already on Thursdays. Friday IV differs significantly from other days also in theory. Ceteris paribus, the option price at the close will be less than the option price at the open. Because at the close we are closer to the expiration of the contract, but time-to-maturity in the IV model (in this case Equation 4) is “updated” only at the beginning of a trading day. This effect emphasizes on Fridays, because of two days of inactivity over the weekend.

F-test for equal means reject the null hypothesis, and hence show that the mean close-to-close returns are not equal for different days. Especially, Monday mean seem to differ from other days. However, the F-test cannot reject hypothesis of equal mean changes from Tuesday to Friday. Hence, while it seems that IV clearly decreases at the end of the week, F-tests cannot confirm this statistically. Table 3 presents the daily mean returns during and after trading days:

Table 3 – Mean VSTOXX rate of returns

Mean close-to-open, open-to-close, open-to-open and close-to-open returns in percentage for VSTOXX during the in-sample period January 11th – August 31st. Close-to-open returns are presented under the day of the close. Close-to-close returns are presented under the day of the "second" close. F-test of whether the five weekday (F_5) means are equal, of whether the Tuesday to Friday means ($F_{5\text{-Monday}}$) means are equal, and of whether Monday to Thursday means ($F_{5\text{-Friday}}$) are equal. F-values which reject the null hypothesis on 1% level are marked with one asterisk, on 5% level are marked with two asterisks and on 10% level with three asterisks.

	Monday	Tue	Wednesday	Thursday	Friday	F_5	$F_{5\text{-Monday}}$	$F_{5\text{-Friday}}$
Close-to-open	-0.701	-0.032	-0.895	-0.509	3.396	8.95*	9.99*	0.64
-Hourly [a]	*-0.045*	*-0.002*	*-0.058*	*-0.033*	*0.053*	-	-	-
Open-to-close	-1.071	0.908	0.528	-0.992	-1.516	2.32***	2.31***	1.85
-Hourly [a]	*-0.143*	*0.121*	*0.070*	*-0.132*	*-0.202*	-	-	-
Open-to-open	-1.771	0.876	-0.367	-1.501	1.880	6.27*	7.73*	1.28
Close-to-close	2.325	0.207	0.495	-1.887	-2.025	5.47*	1.460	7.19*

[a]) Hourly changes are calculated with formula: ΔIV / hours = hourly change. There are 8.5 trading hours Monday through Friday. Thus, the overnight (close-to-open) period is 15.5 hours Monday through Thursday and 63.5 (=15.5+48) hours over the weekend. Hence, the changes are not actually average hourly changes. This would not in this case be practical, because hourly returns cannot be calculated for overnight period and the only purpose of these numbers is to compare the relative changes between these two periods.

When looking more closely, the mean return during the Monday trading (open-to-close) is actually negative. Figure 9 (in the next 5.1.2 section) demonstrates the cumulated intraday returns for all weekdays in VSTOXX. However, it also illustrates the fact that VSTOXX slightly rises on Monday trading, but then starts declining rapidly before the close. It seems that the large rise in IV during the weekend is partly canceled during that time. Hence, it seems that while the close-to-close change is positive, the change actually occurs on weekend. Options are often used for hedging the risk over the weekend. Thus, many investors might want to sell option positions on Monday when the markets open again, which decreases the IV. On other weekdays the open-to-close and close-to-close returns receive similar signs. Open-to-close returns are positive on Tuesdays and Wednesdays, but negative on Thursdays and Fridays. Furthermore, F-tests for equal means indicate that the daily open-to-close means are non-equal at 90% confidence level. Friday open-to-close returns are found to differ statistically the most from other open-to-close returns.

Overnight changes are larger than close-to-open changes, especially over the weekend. But note that the overnight hourly change is clearly smaller than the hourly changes during the periods of active trading, because the overnight period is 15.5 hours long during the week and 63.5 hours over the weekend, respectively. Thus the "average" hourly change is larger on trading period than on non-trading periods on all days.

The weekday dummies confirm the results obtained with F-tests of the average returns. IV drops significantly during Friday and rises on Monday. Dummy coefficients and their t-values are presented in Table 3. The positive Monday and the negative Friday dummies are significant at 99% confidence level in both in-sample datasets. The Monday dummy is positive, because the average change during the day on 1-minute intervals is positive, even though the change during the day is negative. Tuesday and Wednesday dummies were both positive, but they were not statistically significant. Thursday dummy was negative, but statistically significant at 90% with 1-minute intervals. The dummy for 10-minute data was as well negative, but not statistically significant. Hence, the weekday dummies confirm the story of weekly IV pattern.

Table 4 – Weekday and hour dummies

Dummy variables regressed on ln (VSTOXX change). T-values with one asterisk indicate statistical significance at 1% level, two asterisks indicate significance at 5% level, and three asterisks indicate significance at 10% level.

	Panel A: 1-minute VSTOXX		Panel B: 10-minute VSTOXX	
	Coefficient	t-Value	Coefficient	t-Value
Monday	0.00005	2.81*	0.0005	2.56*
Tuesday	0.00002	0.84	0.0002	0.76
Wednesday	0.00002	1.27	0.0002	1.14
Thursday	-0.00003	1.80***	-0.0003	-1.63
Friday	-0.00006	-3.07*	-0.0006	-2.79*
9:00	0.00003	1.00	0.0003	0.94
10:00	0.00001	0.58	0.0001	0.25
11:00	-0.00002	-0.74	-0.0001	-0.41
12:00	0.00008	0.33	0.0001	0.37
13:00	0.00002	0.70	0.0000	0.19
14:00	0.00006	2.71*	0.0007	2.82*
15:00	-0.00002	-1.05	-0.0001	-0.58
16:00	-0.00003	-1.20	-0.0002	-0.94
17:00	-0.00010	-3.03*	-0.0009	-2.96*
9:30[a]	0.00020	3.80*	0.00040	0.89
Friday 9:30[a]	-0.00028	-2.43**	-0.0065	-8.51*

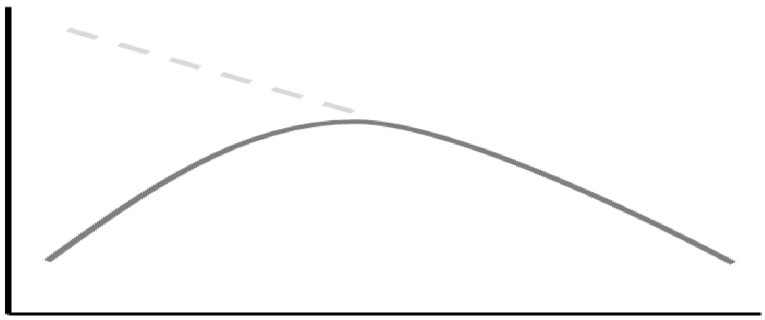
[a]) In 10-minute data the 9:30 dummy is observations at 9:20, 9:30 and 9:40, in 1-minute data it includes all observations between 9:25 and 9:35

5.1.2 Intradaily patterns

Intradaily patterns in IV are next examined. Stock prices tend to follow U-shaped pattern during the trading day. Roughly speaking implied volatility form an inverted U-shaped pattern. On average, IV decreases during the first hour of trading, and then slightly rises for several hours during the day, but then decreases again during the last hour of trading. The declining IV before the close can be explained with the similar explanation as the Friday decline. The equation for VSTOXX does not perceive the decreasing time-to-maturity. Option traders naturally adjust the time-to-maturity dynamically and hence option prices (ceteris paribus) decrease over the day. Thus, the lower option prices reflect to IV. However, the increasing volatility during the trading day is actually inconsistent with decreasing time-to-maturity. If the formula misspecification would be correctly taken into account among option traders and investors, IV declined throughout the trading day. Clearly this is not the case. Thus, the increase during the middle of the trading day must be explained by some other reason. Demand for options must be at the highest during the middle of the trading day. One possible reason for this might be that because derivatives including options are often used for hedging e.g. over-night positions. Investors/traders might then want to sell the hedges, which were taken for the night, in the mornings. Thus, the selling pressure would cause IV to decline in the mornings. If the selling and buying were equal in the mornings, IV should be the highest in the mornings and then decline. Figure 8 demonstrates how the observed line (inverted-U) and the theoretical line (the dash line) meet at the middle of the trading day after separating at the open. Then the both lines continue to decline through the rest of the trading day.

Figure 8 – Demonstration of observed and theoretical intraday implied volatility

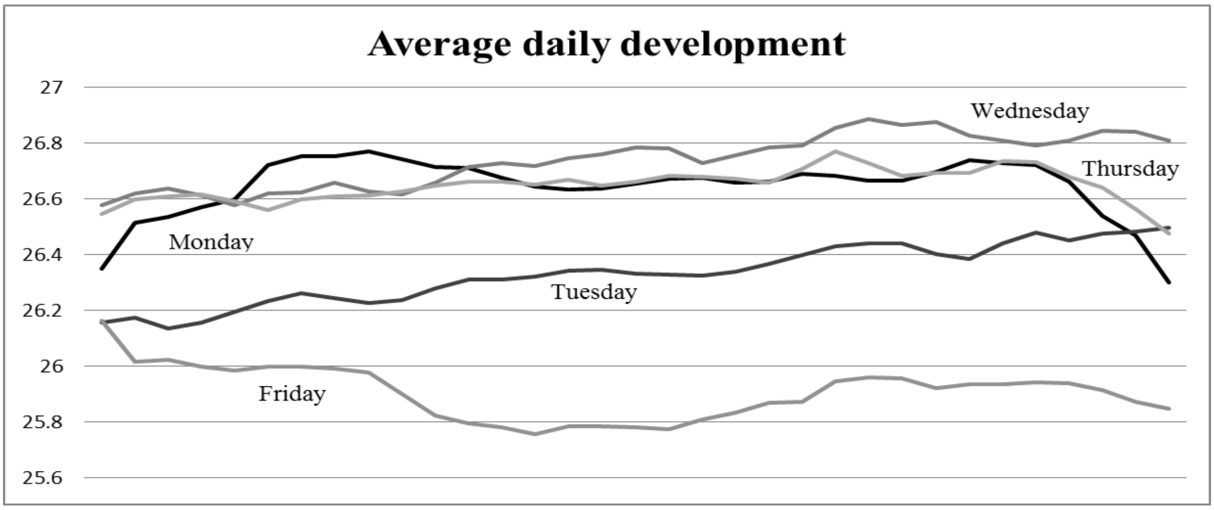
The figure demonstrates the observed inverted U-shaped pattern in IV (roughly speaking). Additionally, the dash line demonstrates the IV in theory, if only the formula misspecification problem is accounted.



Alternatively, the midday pattern might be driven by stock traders. E.g. Chan et al. (1993) find that stocks lead options. Several studies (see, e.g. Jain and Joh, 1988) report that stock prices and volumes decline during the middle of the trading day. Furthermore, IV tends to move to opposite direction than the stock markets. Thus, stock markets might drive the IV during the midday to opposite direction then the stock markets. The question, whether the pattern is driven by stocks are simply an independent patterns, was left for future research.

Figure 9 – Cumulated mean 15-minute intraday returns by weekday

The accrued return is the average return experienced by VSTOXX. Presented as 15-minute averages calculated from the 1-minute dataset. From 9:00 CET to close at 17:30 CET during all 164 trading days



F-tests (presented in Table 4) confirm that mean returns at 15-minute interval are not equal in all intervals on Monday at 95% confidence level. On Mondays IV increases during mornings and middays, but then decreases rapidly during last few hours of trading. Mean returns of 15-minute intervals and F-test for inner mean returns support the story. Figure 9 and Table 4 demonstrates how drastically VSTOXX starts declining on average about 90 minutes before the close. The decrease is most likely derived from the VSTOXX formula problem discussed earlier. The increase during the majority of the Monday trading day could not be explained. Monday average change with 1-minute interval is positive, but the drop at the end of the day is so drastic that the cumulative 1-minute returns from Monday are negative. I made up two rational explanations. First, the markets “recover” the IV which clearly declined at the end of previous week. Second, the increase is driven by stock market patterns. The stock markets tend to decline on Mondays. Declining stocks naturally drive IV higher.

On Tuesdays and Wednesdays IV rises slowly but evenly through the trading days. Actually, on Tuesdays the decline before the close does not occur, as demonstrated in Figure 9. On Wednesdays however, IV seems to decline before the close. The incline then continues through Thursday day, but then IV starts declining couple of hours before the Thursday close. IV then continues to decline throughout the Friday trading. From Tuesday to Thursday, mean returns were found to be equal for all 15-minute intervals, according to the F-tests. However, T-tests with open and close returns compared to rest of the trading day indicate that mean returns are not equal with remaining day on Wednesday and Thursday closes.

F-tests for equal means in all 15-minute intervals indicate Friday means to be non-equal and at 99% confidence level. Furthermore, Friday open mean returns are clearly non-equal with the rest of the day mean returns, according to the T-tests. The declining of IV does not seem to accelerate towards the end of Friday trading, but it declines pretty linearly through the trading day. There are two possible reasons for this. Firstly, it might be the case that markets over-react to the effect earlier on the day and thus the declining is stable throughout the day. Secondly, demand on options probably increases before the weekend, because investors are seeking for portfolio insurance. The buying pressure naturally increases the IV. Figure 9 shows how VSTOXX on Fridays heads to opposite direction than other days right after the open.

If one wants to buy implied volatility (take position with options or buy IV derivatives) on any given day, it seems that normally mornings are the best moments to open the (long) position. Naturally on the other hand, if one wants to short IV, afternoons seems to be best moments for shorting.

Earlier literature has found that volumes of options are low at the beginning of the trading. The option trading procedure is slightly different. Additionally, the option markets depend on the largest market makers, who don’t necessary give quotes right away when the markets open. My empirical findings support this, even though direct IV volumes do not exist. Volatility of implied volatility remains very low until CET 9:15, and then increases. This effect is the strongest on Fridays. Overall, standard deviations are very similar within each interval on all weekdays. Unlike in stock markets, volatility of implied volatility seems to follow closely L-shaped pattern. After the rise in the morning, IV then drops towards the mid-day. However, during the “data hour” volatility jumps clearly higher, even though the low level of volatility otherwise remains until 16:00 CET. Low volatility is then followed by modest increase, which however is not even clearly as significant as in stock market.

The mean changes are equal on other days for the inner parts of the day, according to the F-test. Nevertheless, the dummy for the so called data hour is positive and significant indicating that the IV increases. Additionally, volatility of IV increases at the time, especially right after the data releases at 14:30 CET. Hence, the results are mixed. There seems to be some non-equality in “data hour” means and standard deviations, but statistically this cannot be proved. Additionally, F-tests show that mean returns from 11:30 to 11:45 are not equal on all weekdays. During the interval, VSTOXX rises Tuesdays to Thursdays over 0.1%, but also decreases on Mondays and Fridays heavily. Clear reason for this effect was not found.

Hence, Hypothesis 1.1 of weekly patterns and Hypothesis 1.2 of intradaily patterns are both accepted. Besides the calculation method misspecification, I conjecture the same explanation for IV patterns as Sheikh and Ronn (1994) for patterns of option returns and variances. They discussed, based on Back’s (1992) model that strategic behavior by informed and discretionary liquidity traders may induce systematic patterns in independent components of option returns, e.g. in implied volatility. That is traders’ means and needs drive the patterns, and in this case the nature of options as common hedging instruments stand out. Further, if the arrival of private information about the underlying asset is identical across the stock and options markets, then there should be similarities in the behavior of stock returns and IV returns. Additionally, some patterns are opposite of what has been observed in stock markets. Thus, another explanation for the patterns might be that stock markets drive the patterns. If IV was mainly a fear factor for investors, it would form opposite patterns to what has been observed in stock markets. However, thorough investigations of the drivers behind the patterns, is left for future research.

Table 5 – Mean intraday percentage returns over 15-minute intervals by weekdays

The returns are mean returns experienced by VSTOXX within a given 15-minute interval on a given weekday. Arithmetic averages of rate of returns during given interval from all weekdays are also included. F-tests of whether five weekday means are equal (F_5), of whether the Monday through Thursday means are equal ($F_{5\text{-Friday}}$), and of whether Tuesday through Friday means are equal ($F_{5\text{-Monday}}$). On the bottom are F-tests of whether the mean returns on a given weekday are equal within each given 15-minute intervals (F_{34}), and of whether the mean returns are equal in the middle of the trading day (10:00 CET – 16:00 CET). T-tests of whether mean returns after open (open to CET 9:30) are equal to mean return of rest of the day (T_{open}), and of whether the mean returns before close (16:30 CET to close) are equal to mean returns of rest of the day (T_{close}). Rejection at 1% are denoted with one asterisk, at 5% with two asterisk, at 10% with three asterisks. All 164 trading days except one tuesday open after Monday bank holiday, January 11th to August, 31st, 2012.

	Mean returns									
	Monday	Tuesday	Wednesday	Thursday	Friday	Average	STD	F_5	$F_{5\text{-Monday}}$	$F_{5\text{-Friday}}$
Open-9:15	-0.058	0.025	0.009	-0.002	-0.030	-0.011	0.173	**0.66**	**0.73**	**0.69**
9:16-9:30	-0.189	-0.112	0.109	0.010	-0.919	-0.220	0.309	**4.24 ***	**5.64 ***	**0.79**
9:31-9:45	0.184	-0.115	0.025	0.129	-0.044	0.036	0.233	**0.61**	**0.63**	**0.61**
9:46-10:00	0.091	-0.055	-0.115	0.045	-0.030	-0.013	0.223	**0.39**	**0.39**	**0.52**
10:01-10:15	0.144	0.208	-0.100	-0.081	-0.095	0.015	0.213	**1.29**	**1.20**	**1.26**
10:16-10:30	0.094	0.069	0.126	-0.149	0.044	0.037	0.207	**0.26**	**0.27**	**0.31**
10:31-10:45	0.021	0.165	0.118	-0.010	0.060	0.071	0.218	**0.30**	**0.37**	**0.39**
10:46-11:00	-0.105	-0.066	0.050	0.214	-0.018	0.015	0.182	**1.13**	**1.12**	**1.35**
11:01-11:15	0.036	0.051	-0.058	-0.024	-0.061	-0.011	0.180	**0.23**	**0.16**	**0.24**
11:16-11:30	-0.001	-0.107	-0.209	0.032	-0.159	-0.089	0.157	**0.63**	**0.48**	**0.63**
11:31-11:45	-0.130	0.159	0.335	0.187	-0.282	0.054	0.192	**3.84 ***	**4.09 ****	**2.13 *****
11:46-12:00	-0.052	0.120	0.032	0.045	-0.263	-0.024	0.168	**1.48**	**1.91**	**0.47**
12:01-12:15	-0.016	0.052	0.199	0.010	-0.047	0.040	0.151	**0.96**	**0.87**	**0.96**
12:16-12:30	-0.180	0.003	-0.058	-0.146	-0.111	-0.098	0.153	**0.44**	**0.29**	**0.56**
12:31-12:45	-0.078	0.003	0.043	-0.146	0.076	-0.020	0.143	**1.15**	**1.08**	**1.37**
12:46-13:00	0.016	0.133	-0.060	0.153	-0.019	0.045	0.146	**0.56**	**0.58**	**0.68**
13:01-13:15	0.050	0.080	0.163	-0.148	0.121	0.053	0.141	**2.38 *****	**2.72 ****	**3.73 ****
13:16-13:30	0.151	-0.147	0.030	0.059	-0.186	-0.019	0.129	**1.49**	**1.38**	**0.37**
13:31-13:45	-0.057	0.034	-0.125	-0.004	0.101	-0.010	0.156	**0.64**	**0.74**	**0.27**
13:46-14:00	0.061	-0.015	-0.068	-0.098	0.216	0.019	0.150	**1.14**	**1.32**	**0.30**

14:01-14:15	-0.068	0.060	0.182	-0.074	0.091	0.038	0.161	**0.98**	**0.59**	**1.24**
14:16-14:30	0.045	0.162	0.029	0.119	0.070	0.085	0.158	**0.33**	**0.38**	**0.48**
14:31-14:45	0.078	0.146	0.177	0.262	0.086	0.150	0.221	**0.26**	**0.24**	**0.34**
14:46-15:00	-0.007	0.048	0.277	-0.096	0.054	0.055	0.199	**0.83**	**0.84**	**1.21**
15:01-15:15	-0.128	0.013	0.032	-0.260	0.162	-0.036	0.345	**1.14**	**1.24**	**0.76**
15:16-15:30	0.099	-0.037	-0.126	-0.014	-0.158	-0.047	0.154	**0.94**	**0.44**	**0.86**
15:31-15:45	0.175	-0.255	0.014	0.093	-0.043	-0.003	0.199	**1.63**	**1.28**	**2.15 *** **
15:46-16:00	0.052	0.110	-0.255	0.053	-0.092	-0.026	0.207	**0.96**	**1.16**	**1.36**
16:01-16:15	-0.029	0.324	-0.037	0.146	0.048	0.090	0.249	**0.83**	**0.81**	**0.99**
16:16-16:30	-0.121	-0.054	0.109	-0.185	0.031	-0.044	0.231	**0.50**	**0.59**	**0.55**
16:31-16:45	-0.379	-0.029	-0.093	-0.277	0.233	-0.109	0.239	**1.38**	**0.74**	**1.10**
16:46-17:00	-0.430	0.086	0.153	-0.230	-0.338	-0.152	0.208	**3.77 ***	**3.31 ****	**4.09 ***
17:01-17:15	-0.152	0.066	-0.212	-0.212	-0.039	-0.110	0.228	**0.91**	**1.12**	**1.01**
17:15-17:30	-0.189	0.048	-0.167	-0.391	0.023	-0.135	0.212	**2.09 *****	**2.64 *****	**1.80**
$\mathbf{F_{34}}$	**1.51 ****	**0.91**	**1.13**	**1.16**	**2.18***					
$\mathbf{F_{inner}}$	**1.58 ****	**1.03**	**1.02**	**0.90**	**1.02**					
$\mathbf{T_{open}}$	**0.976**	**0.78**	**0.68**	**0.07**	**3.58***					
$\mathbf{T_{close}}$	**1.41*****	**0.28**	**2.31****	**3.09***	**0.58**					

5.2 Modeling VSTOXX

5.2.1 ARMA models

ARMA models fit very well for the intraday implied volatility. Table 6 summarizes ARMA models' coefficients and t-values. The best model in in-sample analysis was found to be ARIMA (1,1,1). T-values of its coefficients were very high and thus coefficients are statistically significant. ARIMA (1,1,1) has clearly the lowest sum of squared residuals and largest R-squared (excluding ARMA model with the level dataset). AIC and BIC values fall very close to each other in all models. Adding more lags to AR and MA did not improve the models and the additional coefficients are not statistically significant. ARIMA (1,0,1), i.e. ARMA (1,1), model was also found to be good, but when considering justifications of suitable data in Section 4.2., ARIMA (1,1,1) is chosen to be the best fit for the data for this purpose. With the wider 10-minute intervals, the results were very similar. Again, ARIMA (1,1,1) was found to be the best fit for the dataset. However, while in 1-minute data the residuals were clearly the lowest in ARIMA(1,1,1) model, the residuals of models with 10-minute data are much closer to each other in all models. Also AIC and BIC values fall very close to each other and thus the ranking of the models with these indicators is not as obvious as it is in the 1-minute data.

Contrary to earlier literature, VSTOXX do not display volatility persistence. ARCH tests and squared residuals both indicate that there are no significant patterns in volatility of volatility. Additionally, Durbin-Watson statistic for all ARMA and variable models fall very close to value two, which signals also that GARCH models should not fit for the data. The explanation for this must be that data with observations closer together have much more white noise in error terms. Naturally, random factors have larger affection to error terms in short-run than in long run. However, I still estimated ARIMA (1,1,1)-GARCH(1,1) and GARCH (1,1) models, which are also presented in Table 4. ARIMA-GARCH model underperformed ARIMA model in R-squared, AIC and BIC. Nevertheless, the GARCH coefficients are significant and thus I include ARIMA(1,1,1)-GARCH(1,1) in the trading simulation.

Table 6 – In-sample ARMA models

The table summarizes the results of ARIMA (1,1,1), ARIMA (1,0,1), ARIMA (1,1,1)-GARCH (1,1), and GARCH (1,1) models. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The models have been estimated for the period of January 11th to August 31st, 2012. Panel A reports results for models with 1-minute interval in observations and Panel B for 10-minute interval, respectively. T-values for the coefficients are reported in the brackets. R-squared, sum of squared residuals (SSR), Akaike information criteria (AIC) and Bayesian information criteria (BIC) for all models.

	ARIMA (1,1,1)	ARIMA (1,0,1)	ARIMA (1,1,0)	ARIMA (1,1,1)-GARCH (1,1)	GARCH (1,1)
	Panel A: 1-minute interval of VSTOXX				
	Coefficient (t-statistic)	**Coefficient (t-statistic)**	**Coefficient (t-statistic)**	**Coefficient (z-statistic)**	**Coefficient (z-statistic)**
c	-	3.2568	-	-	-
	-	*(16.91)*	-	-	-
Ø	0.8763*	0.99987*	0.0350*	0.7756*	-
	(70.56)	*(17462.91)*	*(10.02)*	*(174.95)*	-
θ	-0.8406*	0.0335*	-	-0.7203*	-
	(-60.20)	*(9.58)*	-	*(-146.16)*	-
C (GARCH)	-	-	-	0.0000	0.0000
	-	-	-	*(541.10)*	*(574.27)*
RESID (-1)	-	-	-	0.7650*	0.6872*
	-	-	-	*(624.81)*	*(675.39)*
GARCH(-1)	-	-	-	0.4148*	0.4148*
	-	-	-	*(534.76)*	*(591.79)*
R-squared	0.00547	0.99975	0.00123	0.004777	-0.000004
SSR	0.3098	0.3779	0.3779	0.3100	
AIC	-9.6427	-2.8709	-9.4439	9.7738	-9.7702
BIC	-9.6424	-2.8706	-9.4440	9.7731	-97699
	Panel B: 10-minute interval of VSTOXX				
	Coefficient (t-statistic)	**Coefficient (t-statistic)**	**Coefficient (t-statistic)**	**Coefficient (z-statistic)**	**Coefficient (z-statistic)**
c	-	3.2590*	-	-	-
	-	*(65.50)*	-	-	-
Ø	0.3646*	0.9982*	0.1072*	0.2820*	-
	(4.15)	*(1516.77)*	*(9.78)*	*(3.68)*	-
θ	-0.2592*	0.0956*	-	-0.1819*	-
	(-2.84)	*(9.07)*	-	*(-2.34)*	-
C (GARCH)	-	-	-	0.00001*	0.00001*
	-	-	-	*(42.57)*	*(50.22)*
RESID (-1)	-	-	-	0.2265*	0.2426*
	-	-	-	*(44.57)*	*(53.40)*
GARCH(-1)	-	-	-	0.6917*	0.6802*
	-	-	-	*(135.07)*	*(150.33)*
R-squared	0.01267	0.997026	0.01148	0.12403	-0.000003
SSR	0.4516	0.4521	0.4521	0.4517	0.4574
AIC	-6.973	-6.972	-6.972	-7.034	-7.029
BIC	-6.974	-6.969	-6.970	-7.029	-7.027

5.2.2 Variable analysis

Next I examine the significance of economic/financial variables. All of the variables except EUR/CHF currency rate are significant when regressed on logarithmic first differences of VSTOXX. Even though the coefficients of the variables are in many cases significant, the models cannot generally compete with ARMA models. When comparing residuals of the models, ARMA models outperform simple variable and ARIMAX models in both of the datasets. R-squared, AIC and BIC values give mixed results. Variable models receive better R-squared values, but then again ARIMA (1,1,1) model receives the best AIC and BIC values. Furthermore, all these values fall very close to each other, and thus superiority between the models cannot be proved by them.

T-values of coefficients are presented in Appendix 1 and Appendix 2. The significance of the coefficients for economic/financial variables is in contradiction to existing literature. Most of the earlier literature has not found economic or financial variables to be significant. The reason for my findings is most likely that widely recognized spill-over effects disappear quickly. Thus, in intraday data there can be seen some spillover effects across different markets, but in interday data spillover effects have already disappeared. E.g. Engle and Susmel (1994) provide evidence for this: they found volatility spillovers between New York and London to last only one hour.

However, when including the variables in the model some of the coefficients lost their statistical significance. That indicates that they cannot provide additionally information with other variables and AR and MA coefficients. Thus, it seems unnecessary to include these variables in the model and they were dropped out.

EUR/CHF exchange rate is not significant, which was expected as the Swiss National Bank (SNB) set a minimum exchange rate of 1.20 to the Euro in 2011. Thus, the volatility of the exchange rate disappeared and the changes nowadays are so small that the coefficient is not significant when regressed on VSTOXX. Change in gold spot rate is significant when regressed alone but not in the model. First lag of DAX, EURO STOXX 50 and STOXX EUROPE 600 coefficient are found to be significant. Thus, they indicate spillover effects exist in intraday data. All three indices indicate that after a drop in equity markets the VSTOXX rises, and other way around. Including three pretty similar variables might be questionable but they all can provide divergent information. EURO STOXX 50 is the underlying for the options where from VSTOXX is derived. Thus, it indicates general direction of VSTOXX. DAX is another blue-chip index, but from different markets. Hence, it is similar index but consist (mainly) of different stocks. It is also the second most followed index in Europe. STOXX EUROPE 600 is much wider index than the EURO STOXX 50, and can provide information on general stock market volatility. After all, EURO STOXX 50 is very bank driven index. EUR/USD currency rate was also significant. The coefficient was negative indicating that when USD appreciates, volatility increases. This is rational because when uncertainty increases in markets USD is often used as a safe haven.

Day-of-the-week dummy variables give expected results (see, Table 4). On Mondays IV increases and the dummy is statistically significant and on Friday dummy is significant and negative. Tuesday to Thursday the change is not statistically significant, but the signs of coefficients were expected. Hour dummies were mainly statistically insignificant. Open hour coefficient was positive as expected, but it is so small that the statistical significance is not achieved. Earlier literature has found that trading volume is very low at the open of option trading and then increases later in the morning. Thus, the insignificance of the opening hour dummy is expected. The 9:30 dummy for values between 9:25 and 9:35 CET is significant, which was found to be the point where trading increases. The dummy coefficient is positive indicating that IV rises. However, on Fridays IV seems to decrease at this point. Thus, I also included dummy variable for Friday 9:30, which has a significant and negative coefficient. The mid-day dummies were insignificant except the dummy for “data hour” 14:00-15:00 CET. The coefficient was positive indicating that implied volatility increases. This was also the indicated result, because major macro-economic data is released in the US, which often causes turbulence in stock markets. The close dummy has clearly negative coefficient indicating that IV decreases towards the end of the trading day as was already discussed.

Table 7 – In-sample economic variable models

The table summarizes the results of variables models and the combined ARIMAX (1,1,1) models. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The models have been estimated for the period of January 11th to August 31st, 2012. Panel A reports results for models with 1-minute interval in observations and Panel B for 10-minute interval, respectively. T-values for the coefficients are reported in the brackets. R-squared, sum of squared residuals (SSR), Akaike information criteria (AIC) and Bayesian information criteria (BIC) for all models.

	Variable Model	ARIMAX (1,1,1)	ARIMAX (1,1,1) a	Variable Model	ARIMAX	ARIMAX (1,1,1) a
	Panel A: 1-minute interval of VSTOXX			Panel B: 10-minute interval of VSTOXX		
	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (z-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (z-statistic)
ø	-	-0.2883*	-0.2302*	-	0.2985*	0.2975*
	-	*(-3.14)*	*(-3.29)*	-	*(3.78)*	*(3.75)*
θ	-	0.2526*	0.1821*	-	-0.1879**	-0.1873**
	-	*(2.69)*	*(2.54)*	-	*(-2.23)*	*(-2.19)*
EURO STOXX 50 (-1)	-0.7471*	-0.7826*	-0.3613*	-1.4835*	-1.4794*	0.1377**
	(-18.02)	*(-18.88)*	*(-18.39)*	*(-13.31)*	*(-13.27)*	*(2.19)*
STOXX EUROPE 600 (-1)	0.4793*	0.4303*	-	-1.4436*	-1.4395**	-
	(9.06)	*(7.96)*	-	*(-9.59)*	*(-2.36)*	-
DAX (-1)	0.2387*	0.2117*	-	-0.4315*	-0.4300*	-
	(6.84)	*(6.02)*	-	*(-4.79)*	*(-4.77)*	-
EUR/USD (-1)	-0.1284*	-0.1510*	-0.1524*	-0.6660*	-0.6663*	-0.1635
	(-3.65)	*(-4.28)*	*(-4.39)*	*(-7.68)*	*(-7.68)*	*(-1.46)*
D(Mon)	0.0001*	0.00005**	0.0001**	0.0003**	0.0003**	0.0006*
	(2.61)	*(2.52)*	*(2.49)*	*(2.36)*	*(2.40)*	*(3.13)*
D(14:00)	0.0001**	0.0001**	0.0001**	-	-	-
	(2.35)	*(2.34)*	*(2.38)*	-	-	-
D(17:00)	-0.0001	-0.0001*	-0.0001**	-0.0005**	-0.0005**	-0.0008*
	(-2.60)	*(-2.59)*	*(-2.53)*	*(-2.50)*	*(-2.57)*	*(-3.01)*
D(09:30)	0.0003*	-0.0003*	0.0003*	-	-	-
	(5.27)	*(5.24)*	*(5.14)*	-	-	-
D(Fri09:30)	-0.0006*	-0.0005*	-0.0005*	-0.0054*	-0.055*	-0.0043*
	(-4.37)	*(-4.41)*	*(-4.42)*	*(-10.64)*	*(10.51)*	*(-6.24)*
R-squared	0.0085	0.0055	0.0075	0.5594	0.0162	0.0158
SSR	0.3752	0.3749	0.3755	0.1975	0.5887	0.5889
AIC	-9.4512	-9.6427	-9.4502	-7.7989	-7.0169	-7.0169
BIC	-9.4501	-9.6424	-9.4491	-7.7920	-7.0104	-7.0117

[a]) STOXX EUROPE 600 and DAX excluded. Their coefficients received unexpectedly a positive value, which seems to be compensated with higher EURO STOXX 50 coefficient. Thus, I tested an alternative model where EURO STOXX 50 is the only stock market index.

With the wider 10-minute intervals the results were very similar. All the economic/financial variables that were significant when regressed on VSTOXX in 1-minute data were found to be significant in 10-minute data as well. Furthermore, the coefficient of the gold price was not found to be significant when included in a variable or ARMA model. Thus, it was dropped out from the models. From the dummy variables, the 9:30 dummy was not significant, but otherwise the coefficients and their significances were similar in both datasets. Hence, the 9:30 dummy is excluded from the regressions. However, it must be noted that the dummies were not totally similar, as described in Table 4. When regressing all the significant variables with 10-minute datasets, coefficient of dummy for 14:00 CET receives much lower t-value than with 1-minute data. The null hypothesis of coefficient to be zero cannot be rejected and I dropped this variable from the regressions, as well.

5.2.3 Forecasting accuracy

Directional accuracy of the models is the best way to rank the models, because the purpose of the model is to forecast direction of change in IV. Table 8 presents the results of models' directional accuracy. ARIMA(1,1,1) and ARIMA(1,1,1)-GARCH(1,1) are the best models to forecast direction of intraday IV. Their accuracy is over 50% at over 99% confidence level. However, they do not reach as high accuracy as the interday IV models in e.g. Ahoniemi (2009). Naturally however, these models are not really comparable since the sample period and the underlying of IV are totally different. The variable models and ARIMAX(1,1,1) models forecast the accuracy correctly every second time. Thus, variable models accuracy is equivalent to accuracy of random guess or coin toss. Furthermore, the best ARIMAX model is a model that includes only the significant dummy variables, but not economic/financial variables. The combined ARIMA and dummy model clearly outperforms the other variables models in both of the datasets. Hence, it seems that while including the economic/financial variables clearly harm the directional accuracy power, this is not the case with the hour and weekday dummies. However, the dummies cannot either improve the models. The reason for irrelevancy of the dummies is that the dummy coefficients are very small and thus they do not change the forecast in either direction. The final statement is that using any kind of explanatory variable is not useful for intraday implied volatility models.

The models seem to forecast direction slightly better when IV decreases. Especially, the variable models performed better forecasting decreasing IV. Pure ARMA model performed almost similarly in both directions. However, it is notable that during the out-of-sample period VSTOXX in general decreases. Hence, most of the observations, about 51.4%, were negative. This might cause the models, which have no forecasting power, to perform better with negative forecasts.

Table 8 – Directional accuracy of forecasts

The table describes the directional accuracies of forecasts provided by six models. The situation is comparable to a coin toss. It only describes whether the model forecasts the direction of change in VSTOXX correctly. Thus, expected accuracy of a random forecast is 50% and the larger value is the better the forecasts are. T-values for hypothesis of results to equal to50% are presented in the brackets. One asterisk denotes rejection at 1%, and two asterisks at 5%, respectively.

	ARIMA (1,1,1)	**VARIABLES model**	**ARIMAX (1,1,1)**	**ARIMAX (1,1,1)a**	**ARIMAX (1,1,1)b**	**ARIMA (1,1,1)-GARCH(1,1)**
1-minute	53.4 % *	50.2 %	49.6 %	49.7 %	53.0 % *	53.2 % *
	(12.00)	*(1.04)*	*(-1.04)*	*(-0.70)*	*(10.77)*	*(11.54)*
10-minute	51.7 % **	50.0 %	49.7 %	50.8 %	51.1 %	52.6 % *
	(2.01)	*(0.09)*	*(-0.23)*	*(1.03)*	*(1.33)*	*(3.03)*

[a]) ARIMAX model where DAX and STOXX EUROPE 500 indices are excluded as described in Table 7.
[b]) ARIMAX model where the only explanatory variables are weekday and hour dummies. The dummies used in 1-minute model were the dummies for Monday, Thursday, Friday and 9:30 CET.

Thus, Hypothesis 2.1, of whether VSTOXX can be modeled and forecasted, is accepted. The directional accuracy is above 50% in ARIMA(1,1,1) and ARIMA(1,1,1)-GARCH(1,1) models and hence they, statistically speaking, are able to provide better than average forecasts for IV changes. **However, Hypothesis 2.2, of explanatory and dummy variables' suitability for modeling, is rejected.** Neither hour and weekday dummies nor economic variables can provide additional information when forecasting direction of implied volatility. The economic/financial variables actually clearly make the models worse than, if they were excluded.

5.2.4 Trading opportunities

Because of the lack of quotes for every minute in the intraday VSTOXX futures data, proper trading simulation cannot be completed. Nevertheless, I simulated a few trading strategies, which do not provide totally robust results, but give some insights of the possible trading results. These simulations indicate that the ARIMA (1,1,1) would provide economic profits in some strategies, even after transaction costs. For instance, I used a strategy, where a trader opens a new position every minute according to the forecasted direction. The strategy is not actually that far-fetched. The time-series is stationary, and thus the position is eventually closed when the IV returns to "equilibrium". Additionally, these patterns that differ from "equilibrium" are exactly what are forecasted. However, these simulations do not actually tell anything about the accuracy power of the model with 1-minute intervals. Thus, it seems unnecessary to report and pay closer attentions to these results. The only option for evaluating the profit providing abilities of models is to estimate it myself, without any empirical evidence. I thus then examined the statistical features of the index and futures data. When considering bid-ask spread of VSTOXX futures, profitable trading at high-frequency seems impossible. Average bid-ask spread during out-of-sample period was 0.11, while the median was 0.10 points. It means that when buying/selling future contract, the position is on average 0.11 points, or 11 euros, on loss. Thus, an investor needs IV, or the IV futures, to change 0.11 points to expected direction to even get to break even. Absolute median change in VSTOXX with 1-minute intervals is 0.01 and with 10-minute intervals 0.07 points or per cents. Thus, the median change, even with 1-minute interval, does not cover the bid-ask spread. Additionally, the minimum change in futures is 0.05, which means that the smallest changes in VSTOXX do not even reflect to the futures. **Hence, profitable high-frequency intraday implied volatility trading with a model forecasting the direction correctly 53 times out of hundred cannot be possible.** Even with a model, which has perfect directional accuracy, it would be extremely difficult. Since, non-profitability is also in-line with previous literature[9] I have strong a belief in my conjecture, despite of the lack of robust empirical evidence.

[9] See, e.g. Jensen (1965)

6. Summary

Implied volatility has drawn a lot of attention during the last few decades among academics. The majority of the literature has focused on examining IV as forecast for future realized historic volatility or used IV to explain abnormal market returns and macroeconomic changes. Only a few studies have examined IV and whether it can forecasted. Furthermore, patterns of intradaily and/or interdaily implied volatility have not been the focus in earlier literature. My conjecture is that implied volatility has not been important factor in financial markets until the last decade or so. Thus, because IV has been such a minor thing, it has not interested academics. However, during the last decades, IV indices as fear factors have spread to big public. Additionally, implied volatility itself is nowadays tradable via IV futures. The framework for my thesis was to examine implied volatility patterns on intradaily level. Then I used these results to model intraday implied volatility with two datasets. The theoretical framework for implied volatility patterns are drawn from stock and option market return. The methodology for IV patterns is mainly motivated by Harris (1986). When it comes to IV modeling and forecasting, my thesis is motivated by Harvey and Whayley (1992) and Ahoniemi (2009). Earlier literature has found ARMA models to fit for implied volatility time-series. IV series generally are stationary and display high autocorrelation. In my study, I have provided a more elaborate approach on the IV with more recent data. The intraday dataset has not been studied before in IV study with this kind of focus. Overall, my thesis focuses on discovering intraday implied volatility patterns and characteristics. And hence it focuses on understanding intraday IV itself, instead of using IV to explain some other phenomenon, which is the main focus in earlier academic literature.

6.1 Main findings

My empirical findings support **Hypothesis 1.1 of weekly patterns and Hypothesis 1.2 of intradaily patterns, hence both are accepted.** The most obvious pattern is that IV declines on Fridays, but then again recovers during the weekend and during the beginning of Monday trading. Implied volatility declines on Fridays, because of time to maturity of options decrease. Less time to maturity makes the option prices to drop. Nevertheless, the time-to-maturity in formula for VSTOXX is not updated until the following Monday. Thus, the lower option prices, ceteris paribus, cause IV to decrease, because of mechanical reasons.

Measuring close-to-close I confirm the findings of earlier IV studies: IV tends to rise on Mondays, and then continue to rise slightly from Tuesday to Thursday, but then drastically decline on Friday. F-test for equal means between trading days, rejects the null hypothesis, and hence support that the mean close-to-close changes are not equal for each trading day. These results are also supported by the weekday dummies. However, when examining more closely it is obvious that open-to-close changes are not similar. Majority of the weekly implied volatility patterns described earlier seems to occur during the non-trading periods. The declining IV on Fridays is obvious also during the trading day, but for instance on Mondays the mean change over the whole trading day is actually negative. Nevertheless, overnight changes were found to be smaller than the changes during trading days. Similar results regarding the magnitude of changes overnight have been earlier reported in stock market pattern studies. Additionally, on Thursdays IV declines close-to-close and open-to-close. The weekend effect seems to start already on Thursday afternoon.

The most drastic intraday pattern is similar as the declining IV on Fridays: implied volatility tends to decline towards the end of a trading day. The explanation for this is similar as with declining IV on Fridays. Maturity becomes nearer, but the time-to-maturity is not updated in VSTOXX formula before the next morning. Hence, the pattern is mechanical. Additionally, IV declines during the first hour of trading, and then slightly rises for several hours during the trading day before the close. The rising IV during the trading day is not consistent with the formula misspecification, but can be explained by stock prices. Stock prices follow a U-shaped pattern. The decreasing stock prices then reflect to higher IV at the bottom of the “U”. Furthermore, unlike in stock markets, volatility of implied volatility seems to follow closely L-shaped pattern. As reported by many option studies (see, e.g. Stephan and Whaley, 1990), the trading with options starts properly only some 30 minutes after the start of the official trading. This seems to be the case with IV as well; volatility of IV is very low during the first 30 minutes of the trading day. Additionally, F-tests confirm that mean changes at 15-minute interval are not equal during the trading day on Monday at 95% confidence level and on Friday at 99% confidence level. Furthermore, Friday open mean returns are clearly non-equal with rest of the day and the returns between were not equal according to the T-tests. The declining of IV does not seem to accelerate towards the end of Friday trading. Which again is against what would be supposed based on the time-to-maturity problem. Additionally, there seems to be some non-equality in “data hour” means and standard deviations, but statistically this cannot be proved.

When measured with coefficients significance, forecasting of directional accuracy and sum of residuals, ARMA models fit well for the intraday VSTOXX time-series – as expected. **I thus accepted the Hypothesis 2.1 of whether VSTOXX can be modeled and forecasted.** ARIMA (1,1,1) was found to be the best model when comparing residuals of the regressions. Additionally, ARIMA (1,1,1) forecasted direction of VSTOXX with highest of all accuracy, 53.4%. As expected, adding ARMA extension to ARMA models do not provide any improvement for models. VSTOXX do not display volatility persistence according to ARCH tests, squared residuals and Durbin-Watson statistics. Proper trading simulation could not be conducted, but most likely intraday models cannot provide any economic profits after transaction costs.

Hypothesis 2.2, of explanatory and dummy variables' suitability for modeling, was rejected, since neither the economic variables nor the hour/weekday dummies did not improve accuracy or models. All but variables, except EUR/CHF currency rate variable, were significant when regressed on VSTOXX. Additionally, several hour and weekday dummies were also found significant. However, when economic and ARMA variables were combined, the models did not perform well anymore. In directional forecasting accuracy both plain variable model and combined ARIMAX model performed very poorly. ARIMAX models lost all their forecasting power compared to the ARIMA (1,1,1) model. None of the models including economic variables could not outperform coin toss in IV direction forecasting. Hour/weekday dummies on the other hand did not worsen the ARIMA (1,1,1), but they did not either provide any assistance.

Trading strategies based only on these forecasts would not be profitable because of transaction costs and the bid-ask spread. However, profits may be made when there are other reasons to trade. Purchasers/sellers of options and investors who wish to hedge volatility or take view on volatility may wish to time the transactions according to the clear IV patterns that were found. For example, investors should rather buy the options or implied volatility on mornings and sell on afternoons.

Table 9 – Summary of hypotheses

The table summarizes hypotheses and whether the hypothesis is accepted or rejected.

Hypothesis 1.1	Day-of-the-week effects exist and thus implied volatility is not equal each trading day	**Accepted**
Hypothesis 1.2	Intraday patterns exist and thus implied volatility is not equal each trading hour	**Accepted**
Hypothesis 2.1	Implied volatility of EURO STOXX 50 can be modeled and forecasted with 1-minute and 10-minute interval in observations.	**Accepted**
Hypothesis 2.2	Previous (T-1) observations of the economic/financial variables and the dummy variables for intraday patterns contain useful information on implied volatility at intraday level.	**Rejected**

6.2 Conclusions and suggestions for future literature

What it comes to intraday VSTOXX modeling and forecasting, I found it to be similar to what earlier literature has found interday implied volatility to be. ARMA models seem to be good fit for the data and external explanatory variables do not improve models. Additionally, intraday patterns exist, but they cannot be exploited in forecasting. The patterns are either due to IV formula misspecification, caused by option/IV traders or driven by stock markets.

Suggestion for future literature is to study the volatility futures, as soon as proper data is available. There are two aspects to study. First aspect is simply to study profit generation of different IV models. Second one is probably more interesting: are the IV patterns included in IV futures prices. If the futures do not take the patterns into account, then a trader can earn from buying/selling futures according to the patterns. That is, a trader might want to sell IV futures on Thursday morning and then buy them on Friday before the close. It is far-fetched that these patterns would not be considered in the prices. Then on the other hand IV markets are not very liquid and thus imperfect. Thus, it seems also impossible that the patterns would be perfectly inside the prices. Secondly, it might be interesting to use some multi-regime time-series models for intraday IV. These models have been found to be good fit for IV data (see, e.g. Ahoniemi, 2009). Additionally, the question for drivers behind the intraday patterns was left for future research. Probably many patterns are driven by IV and option traders, but it however also seems rational that stock markets would drive IV patterns.

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Appendices

Panel A: Summary statistics for VSTOXX: January 11, 2012 to August 31, 2012						
	Levels		Differences		Log differences	
	VSTOXX 1 min	VSTOXX 10 min	VSTOXX 1 min	VSTOXX 10 min	VSTOXX 1 min	VSTOXX 10 min
Mean	26.45	26.45	-0.000034	-0.0003	-0.000004	-0.00001
Std. Deviation	3.65	3.65	-0.0004	0.7946	0.001955	-0.00017
Observations	81539	8241	81538	8240	81538	8240
Min	17.29	17.29	-2.71	-2.71	-0.07	0.14
Max	38.28	38.16	3.73	3.73	0.08	-0.10
Skewness	0.50	0.50	7.43	-1.51	3.45	1.91
Kurtosis	3.04	0.04	687.77	1282.47	274.05	49.68
Jarque - Bera	3406*	343.40*	1590m*	768712	250m*	753128
ADF p-value	0.0812	0.0486	0.0001	0.0001	0.0001	0.0001

Panel B: Summary statistics for financial and macroeconomical indicators (1 min): January 11, 2012 to August 31, 2012						
	EURO STOXX 50	GOLD	EUR/USD	EUR/CHF	DAX	EURO STOXX 600
Mean	2350.22	1641.88	1.28	1.20	6629.97	257.10
Std. Deviation	141.09	56.43	0.04	0.00	292.26	9.44
Observations	81539	81539	81539	81539	81539	81539
Min	2051.28	1529.24	1.21	1.20	5915.39	233.48
Max	2611.15	1790.56	1.35	1.21	7193.98	273.59
Skewness	-0.1422	0.5405	-0.1179	1.0854	-0.2190	-0.4019
Kurtosis	-1.2209	-0.3546	-1.4205	0.0465	-0.9580	-0.7541
t-value	-21.32*	-5.38*	-14.49*	-1.14	-15.94*	-15.41*

Panel C: Summary statistics for financial and macroeconomical indicators (10 min): January 11, 2012 to August 31, 2012						
	EURO STOXX 50	GOLD	EUR/USD	EUR/CHF	DAX	EURO STOXX 600
Mean	2350.24	1641.89	1.28	1.20	6630.07	257.10
Std. Deviation	141.11	56.43	0.04	0.00	292.29	9.45
Observations	8238	8238	8238	8238	8238	8238
Min	2052.81	1529.43	1.21	1.20	5917.09	233.50
Max	2611.15	1789.85	1.35	1.21	7191.01	273.59
Skewness	-0.14	0.54	-0.12	1.08	-0.22	-0.40
Kurtosis	-1.22	-0.35	-1.42	0.04	-0.96	-0.75
t-value	-5.87*	-4.78*	-5.69*	-0.65	-6.26*	-5.74*

Appendix 1: Summary statistics for in-sample period

The table summarizes statistical characteristics of all variables used for modeling. The first-order autocorrelations ρ1, augmented Dickey-Fuller test for unit roots and Jarque-Bera test for normality are also reported. Additionally, t-values for statistical significance of economic/financial variables in modeling VSTOXX are provided. For VSTOXX both level and differenced statistics are provided.

Panel A: Summary statistics for VSTOXX: January 11, 2012 to November 26, 2012						
	Levels		Differences		ln (differences)	
	VSTOXX 1 min	VSTOXX 10 min	VSTOXX 1 min	VSTOXX 10 min	VSTOXX 1 min	VSTOXX 10 min
Mean	25.22	25.24	-0.000089	-0.000894	-0.000004	-0.000039
Std. Deviation	3.86	3.85	0.053837	0.188761	0.002090	0.007298
Observations	111742	11237	111741	11236	111741	11236
Max	38.28	38.16	3.73	3.71	0.14	0.14
Min	17.29	17.29	-2.66	-2.82	-0.11	-0.11
Skewness	0.63	0.63	6.27	1.53	5.70	1.37
Kurtosis	3.06	3.06	731.63	55.45	675.43	51.35
Jarque - Bera	7522*	757*	2470m*	1.3m*	2110m*	1.1m*
ρ1	1.00	1.00	0.04	0.10	0.04	0.10
ADF p-value	0.11	0.08	0.00	0.00	0.00	0.00

Panel B: Summary statistics for VSTOXX futures: September 3, 2012 to November 26, 2012			
	Close	Bid	Ask
Mean	22.20	22.18	22.35
Std. Deviation	1.74	1.71	1.72
Observations	5986	17439	17763
Max	27.70	27.70	27.80
Min	17.45	17.45	17.50

Panel C: Summary statistics for financial and macroeconomical indicators (1 min): January 11, 2012 to November 26, 2012						
	EURO STOXX 50	GOLD	EUR/USD	EUR/CHF	DAX	EURO STOXX 600
Mean	2393.88	1665.09	1.28	1.20	6800.29	260.97
Std. Deviation	141.63	65.85	0.03	0.00	380.00	10.37
Observations	111742	111742	111742	111742	111742	111742
Max	2611.15	1794.05	1.35	1.22	7476.89	276.54
Min	2051.28	1529.24	1.21	1.20	5915.39	233.48
Skewness	-0.59	0.13	-0.29	0.68	-0.15	-0.61
Kurtosis	2.04	1.89	2.00	2.48	1.98	2.36
t-value	-27.36*	-3.20*	-22.24*	-1.24	-21.51*	-21.88*

Panel D: Summary statistics for financial and macroeconomical indicators (10 min): January 11, 2012 to November 26, 2012						
	EURO STOXX 50	GOLD	EUR/USD	EUR/CHF	DAX	EURO STOXX 600
Mean	2393.19	1665.09	1.28	1.20	6797.70	260.91
Std. Deviation	141.55	65.85	0.03	0.00	378.72	10.35
Observations	11236	11236	11236	11236	11236	11236
Max	2611.15	1794.05	1.35	1.22	7473.46	276.46
Min	2052.81	1529.24	1.21	1.20	5917.09	233.50
Skewness	-0.59	0.13	-0.29	0.68	-0.15	-0.61
Kurtosis	2.03	1.89	2.00	2.48	1.99	2.36
t-value	-6.21*	-2.88*	-5.55*	-0.67	-6.10*	-5.99*

Appendix 2: Summary statistics for out-of-sample period

The table summarizes statistical characteristics of all variables used for modeling. The first-order autocorrelations ρ1, augmented Dickey-Fuller test for unit roots and Jarque-Bera test for normality are also reported. Additionally, t-values for statistical significance of economic/financial variables in modeling VSTOXX are provided. Also, the VSTOXX futures during the out-of-sample period are described.