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Dissertation

"Constructing an Implied Volatility Index for the Greek Market"

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Section 1
Introduction

In finance, volatility refers to the standard deviation of the continuously compounded returns of a financial instrument over a specific time horizon. It is often used to quantify the risk of the instrument over that time period and is typically expressed in annualized terms. What makes volatility a subject of extensive research is that, by nature, is unobservable. For this purpose we have to estimate it in some manner. There are two fundamentally different approaches for the determination of volatility. On the one hand, volatility can be determined by measuring the standard deviation of an asset's prices over a given period of time. This method yields the historical volatility (or ex-post volatility). On the other hand, volatility can be measured by the prices of options contracts written upon the asset, i.e. the implied volatility. This method yields the current (ex-ante, or forward-looking) volatility implied by the market.

Implied volatility of an option contract is the volatility implied by its market price based on an option pricing model. In other words, it is the volatility that, when used in a particular pricing model (i.e. Black-Scholes model), yields the current market price of that option. In general the implied volatility of a financial asset is the volatility implied by the options' market prices that are written on it. Implied volatility is a forward-looking measure. It differs from historical volatility because the latter is calculated from the asset's historical prices. In this study we are concerned about implied volatility and in particular about implied volatility indices.

Implied volatility indices are constructed from a basket of options contracts. They represent the forward-looking volatility of an underlying stock index. In this manner is an investor's forecast for the level of the market risk over a specific future horizon (most commonly over the next month).

In the domestic literature, Skiadopoulos (2004) was the first to construct an implied volatility index for the Greek market (named GVIX) for the period October 2000 to December 2002. He followed an altered, for liquidity reasons, Black-Scholes methodology. Siriopoulos and Fassas (2008) also constructed a Greek implied volatility index (named GRIV) for the period January 2004 to December 2008. They followed the new Chicago Board of Options Exchange's (CBOE) VIX methodology.

In this study we also construct an implied volatility index for the Greek market, named VASEX following the recently developed model-free methodology. Our study differs from the Siriopoulos and Fassas (2008) one, in that we apply several filters to our dataset, in order to remove unreliable options prices from our dataset, and from the subsequent calculations. In this way we aim to construct an index as less prone to flaws due to anomalies of the market as possible. Nevertheless, the liquidity of the Greek derivatives market is quite thin, so we cannot have a sufficient number of options with traded volume everyday to get the needed strip of options for the model to work. For this reason, we apply the cubic spline interpolation method in our dataset as proposed by Jiang and Tian [(2005) and (2007)], in order to make our dataset smoothed. As Jiang and Tian (2005) report, this curve fitting procedure for the volatility function does not falsifies the results and makes the volatility function to be closer to the well known volatility smile (or volatility skew, as we are concerned about stock options).

1.1 A little bit of history about Implied Volatility Indices

The idea of the construction of an implied volatility index dates back in 1989, when Brenner and Galai first suggested it. Implied volatility indices are constructed from call and put options contracts. They represent the forward-looking volatility of an underlying stock index. The maturities of the options contracts on the underlying stock index used are the nearby and the second nearby series. To reach to a single value for each day, a procedure of weighting the implied volatilities of the used options takes part. The idea behind this weighting scheme is the construction of a synthetic at-the-money (ATM) option that has a fixed time to maturity of thirty calendar days (or equivalently twenty-two trading days).

Implied Volatility Indices have received an ever-increasing attention of the academic society and the market's practitioners since 1993, when the Chicago Board of Options Exchange (CBOE) introduced the VIX index. The VIX index was the breakthrough in the field, since it was the first volatility index to be introduced by an official exchange and have daily quotes. A unique characteristic of this index was that it was the first one to use options contracts written on a stock index (S&P 100), rather than on individual stocks. In this way, the index reflected the volatility of the whole market (market risk), as proxied by the S&P 100, rather than a stock's risk that contains idiosyncratic risk. The concept of taking into account a stock index is very important because in this way, due to portfolio diversification, the idiosyncratic risk of each stock is eliminated. The systematic risk, that remains, is the one that matters for asset allocation purposes. Since then many studies have been contacted. The index was mainly based on the work of Whaley (1993). Following the example of CBOE, in 1994, the Deutsche Börse also introduced an implied volatility index, named VDAX and in 1997 the French Marché des Options Négociables de Paris (MONEP) two implied volatility indices, named VX1 and VX6. Other exchanges continued and introduced their own implied volatility indices.

The first launched implied volatility index, VIX was constructed using the Black-Scholes (1973) and Merton (1973) model. In this options pricing framework, the variables needed are the spot price of the underlying asset, the strike price of the option contract, the risk-free interest rate of return, the dividend yield of the underlying asset and of course the volatility. Given that all the others variables are known and observable and taking into consideration the market prices of the options as they formed by the demand and supply the only remaining variable is the volatility. By inverting the formula and solving for volatility we extract the so-called implied volatility.

The Black-Scholes model has a set of assumptions that do not match the real circumstances. It assumes that the volatility is constant throughout the life of the option contract, but we know that volatility is a function of the strike price and the time to maturity. Given this fact, the computation of the VIX index requires eight options contracts for each day. Four options, for the near term contracts (i.e. two calls and two puts) and four for the second near term contracts. For all these options the implied volatilities are extracted and a weighting process takes place in order to reach to a single value [for a detailed description of the process, see Whaley, R.E. (2000) "The investor fear gauge"].

Recently, in 2003 the CBOE updated the construction methodology of its volatility index. It shifted to a model-free calculation formula. The idea of a model-free estimation of the implied volatility, independent from an option pricing formula, began with the creation of variance swaps. These products are derivatives that their value depends only on the volatility. The formula underlying the new VIX computation is based on the concept of the fair value of future volatility. It is based on the works of Demeterfi et al. (1999) and Britten-Jones and Neuberger (2000) about variance and volatility swaps.

The need for volatility swaps and in general, volatility derivatives has motivated the researchers to the construction of an implied volatility index. These instruments have payoffs that depend only on the volatility; hence they provide exposure to the realized volatilities of the asset returns. This index serves as an underlying asset, upon which volatility derivatives can be written. The investors willing to deal with them are those who want to hedge the Vega risk (or volatility risk). These products have recently attracted much interest because unlike the traditional derivatives contracts, such as stock options, they do not have exposure on the underlying asset's price fluctuations.

Another important change in the VIX implied volatility index calculation is that it uses options contracts written on the S&P500 stock index, rather than on S&P100. Even though the two stock indices are highly correlated, S&P500 is considered a more appropriate proxy of the United States stock market.

The reasons behind the change in the methodology used to compute the VIX index are the following:

- The old VIX index's economic notion, which is the at-the-money implied volatility, is not explained exactly by a certain theoretical framework except for the Black-Scholes model. In contrast, the new VIX index represents the value of a linear portfolio of options and is theoretically more robust.

- In the old VIX index calculation, was made a conversion of calendar days to trading days, leading to a technical upward bias and rendering the comparison of the implied volatility with the realized volatility impossible.

- The last reason for the change has to do with the concept of variance swaps. The replication of the variance swaps cash flows using the old VIX was difficult. In contrast the new VIX approximates the most these cash flows. This is the reason why volatility derivatives where never written with underlying asset the old VIX, whereas soon after the new VIX was launched it became the underlying asset of volatility derivatives.

The CBOE continues to calculate and maintain the old VIX index based on the S&P 100 (OEX) index option prices. The one thing that has changed is its ticker symbol that is VXO. Simultaneously, the CBOE applied the model-free calculation to the VXN index which was launched in 1997, based on Nasdaq-100 option contracts.

1.2 Related Literature – Some Empirical Findings

There is an extensive and ever growing literature on implied volatility indices. The research has focused its efforts on the properties of these indices and their information content.

A well known characteristic of the implied volatility indices is the negative and statistically significant relationship between the changes in the implied volatility and the returns of the underlying stock index. Researchers such as Whaley (1993, 2000), Giot (2002a), Skiadopoulos (2004) and Siriopoulos and Fassas (2008) have dealt with it. Giot (2002a) studies, for the period 1995-2002 the relationship between the U.S. stock indices, S&P100 and Nasdaq 100 and the implied volatility indices that correspond to them, VIX and VXN respectively. He reports that positive stock index returns lead to decreased implied volatility levels and vice versa. He also reports that this relationship is asymmetric, meaning that the negative stock index returns lead to greater changes in the implied volatility levels than positive returns do. Whaley (2000) also reports this asymmetric relationship with refer to S&P100 returns and VIX changes, over the period 1995-2000. Simon (2003), reports the same findings for the relation of the Nasdaq-100 Index and the VXN index, using a dataset that spans the period January 1995 through May 2002. In the domestic literature, both Skiadopoulos (2004) and Siriopoulos and Fassas (2008) do observe this behavior between the stock index FTSE/ASE-20 and the Greek implied volatility measures that they constructed, namely GVIX and GRIV respectively.

Another aspect with which the literature has dealt is the transmission of the implied volatility across international markets. Gemmill and Kamiyama (2000) study the transmission of the implied volatility among U.S., U.K. and Japan equity markets.

They employ a vector autoregressive (VAR) modeling framework and find that implied volatilities are correlated across markets and the changes of the implied volatilities are transmitted across them. By contrast, they report that the implied skewness of the volatility smile is a local phenomenon. Badshah (2009) studies the volatility transmission among the VIX, VXN, VDAX and VSTOXX indices and finds high correlation between the indices, which indicates that investors' expectations about the future realized volatilities are related across the markets. A fact that suggests to portfolio managers and option traders to incorporate these implied correlations into their models. He also reports that VIX is the most influential index, followed by the VDAX index. Jiang et al. (2009) on a working paper study the spillovers of the implied volatility and the effects of news announcements over the period 2001-2008. They use a sample of eight indices, four U.S. and four European. They report that European volatility indices are led by the U.S. ones and that these spillovers stem mainly from the lagged changes in the implied volatility indices and not from the individual news announcements.

The information content and the predictive power of the implied volatility is also an area of great interest. Canina and Figlewski (1993) report that past volatility subsumes all the information content of implied volatility. They report that their results for the forecasting ability of the past volatility are invariant to whether implied volatility is included as an explanatory variable or not. Christensen and Prabhala (1998) however criticized the results of Canina and Figlewski. They focused on the ability of the S&P 100 index options implied volatility to forecast the future realized volatility. Their sample spanned the period 1983-1995 and they were the first to use non-overlapping data because as they state overlapping data tends to overstate the explanatory power of past volatility. They report that implied volatility does predict future realized volatility in isolation as well as in conjunction with the history of past realized volatility and that implied volatility subsumes the information content of past volatility.

More recently, Jiang and Tian (2005) study the information content of the new VIX index, using data that span the period 1988-1994. They report that the model-free implied volatility contains all the information content of both at-the-money implied volatility and past realized volatility and is a more efficient forecast for future realized volatility. Carr and Wu (2006) study the predictability of realized variance and returns to variance swap investments by using the VIX index and data spanning the period 1990-2005. They report that VIX can predict movements in future realized volatility and that GARCH volatilities do not provide extra information when the VIX index is included as regressor. However they conclude that the predictability of the future realized volatility cannot help in the prediction of excess returns for investing in variance swaps. Areal (2008) also studies the forecasting ability of U.K. market's implied volatility indices, with refer to the realized volatility, over the period 1993-2001. He constructs three indices based on three different methodologies. An index constructed using the CBOE's old methodology (Black-Scholes implied volatility), an index constructed using the model-free methodology and finally one index using a modified at-the-money implied volatility methodology, named alternative interpolation scheme that he proposes due to the limited liquidity of the U.K. market, as compared to the U.S. one. In contrast to other findings, he reports that the realized volatility is a better forecast of the future realized volatility than any of the other indices. He also reports that the model-free implied volatility index is the worst one, in forecasting concerns and he attributes it to the inefficient data on the FTSE-100 index options available to construct such an index.

1.3 Contribution to the existing literature

As mentioned before, there are two studies on the construction of an implied volatility index for the illiquid and thin Greek market. Skiadopoulos (2004) constructed the GVIX index, using Black's (1976) model and Siriopoulos and Fassas (2008) constructed the GRIV index, using the CBOE's new methodology. In their study, Siriopoulos and Fassas (2008) use every available observation even if the prerequisites are not fully fulfilled (for example non zero traded volume) and fill when necessary missing option values using the Put-Call Parity. In this study we construct a new Greek implied volatility index, named VASEX using the CBOE's new methodology, reinforcing it however with a tool provided by Jiang and Tian [(2005) and (2007)]. We use the cubic spline interpolation method to deal with the limited availability of strike prices due to the small size of the market and thus we end up with a smoothed data set. We regard this process necessary since the limited trading on the ADEX's options and the subsequent elimination of options data through the filtering procedure turns the model not functional in a lot of cases.

Finally, we access the information content of the VASEX index and its forecasting ability about the future realized volatility. Toward this end, we construct the GVIX implied volatility index proposed by Skiadopoulos (2004) in order to compare their forecasting ability. Since GVIX is a Black-Scholes implied volatility index we also study whether its information content is subsumed by the model-free VASEX index. This is an argument of great interest, as recently a lot of research is done in this field [see for example Areal (2008)]. However, to the best of our knowledge no previous research exists for the case of the Greek market and is limited for the cases of illiquid and low depth markets.

1.4 Structure of the present study

The rest of the study is structured as follows. First, in section 2 we present the data set and the screening that was made in order to remove unreliable data from our database and keep only those that are considered reliable, meaning that they are less prone to be flawed by anomalies of the market such as mispricing. In section 3, we describe the construction methodology of the Greek implied volatility index, VASEX and we study the properties of the index along with the properties of the underlying stock index, FTSE/ASE-20. In Section 4, we examine the relationship of VASEX with the FTSE/ASE-20, and hence with the Greek equity market. In particular, we test for the existence of the "leverage effect" and whether or not it is asymmetric. We also check the stability of the risk-return relationship and the impact of the Global financial crisis upon it. Then we implement a Granger-causality test to see whether the time series of the implied volatility index can help forecast the stock index returns and vice-versa. Towards the end of the section we test whether VASEX can be characterized as a leading-market indicator. In Section 5, we study the volatility spillovers across international markets via correlation analysis for the implemented indices VASEX, VIX, VDAX, VCAC, VSMI and VSTOXX, a Vector Autoregressive (VAR) model and Granger Causality tests. Finally, in section 6 we examine the relation between realized and implied volatility. The purpose is to access the information content of the implied volatility with respect to the forecast of the future realized volatility. Toward this point, we construct a second implied volatility index (GVIX) for the Greek market following Skiadopoulos (2004) methodology in order to compare their forecasting ability. We also study whether the information content of GVIX is subsumed by the model-free VASEX index. The conclusions of this study are presented in the last section, 7.

Section 2
The Data set and its subsequent screening

2.1 The Data Set

- Options Data

We use daily data on European style options traded on the Athens Derivatives Exchange (ADEX) and written on the FTSE/ASE-20 Index. The Data were obtained from the website of ADEX (www.ase.adex.gr) for the period January 2004 to December 2008. The raw data set consists of the strike prices, the closing prices of call and put options, the traded volume and the open interest for the shortest and the second shortest to maturity option series.

- FTSE/ASE – 20 Index

Daily closing prices of the index for the period January 2004 to December 2008 were downloaded from the DataStream. The FTSE/ASE-20 index is the Greek high capitalization index and contains the twenty largest corporations, with a view to capitalization and merchantability, listed in the Athens Stocks Exchange (ATHEX). This index was introduced in September 1997 and is revised twice a year.

- Interest Rates

We use the EURIBOR interest rate as a proxy of the risk-free interest rate. We obtained the data from DataStream. Daily interest rates for one, two, three weeks and one, two months were obtained. The interest rates for other maturities were calculated with linear interpolation. These interest rates are expressed in a discrete form so in order to convert them to equivalent continuously compounded interest rates we used the following formula:

$$R_c = m \times ln\left(1 + \frac{R_m}{m}\right)$$

Where

R_c : Equivalent interest rate with continuous compounding

m : Times of compounding per annum

R_m : Interest rate compounded m times per annum

However, the effect of any measurement errors in the calculation of the interest rates is small since the rho of out-of-the-money (OTM) options is small.

$$rho = \frac{d\,O_t}{d\,r_{t,T}}$$

- Dividends

The FTSE/ASE-20 Index is a dividend paying asset. Although at first sight we do not need the dividend yield to calculate the implied volatilities using the model-free methodology we do need them in order to check whether the options to be used in the calculations violate the standard upper and lower bounds proposed by Merton (1973).

Unfortunately DataStream or any other database does not provide the data needed, which is the dividend yield on the FTSE/ASE-20 Index. But even if these data were available, these dividend yields would be by nature backward-looking. There is no reason to expect that the actual recorded dividends reflect correctly the expected future dividends at the time that an option is priced. The aim though of this study is to construct an index that reflects the forward-looking volatility based on the expectations of the market participants.

To circumvent this problem and calculate for each day and for each maturity the dividend yield implied by market prices, we follow a method proposed by Sahalia and Lo (1998).

We use the Spot – Futures Parity in order to estimate the unobservable dividend yield. The Spot-Futures Parity is expressed as:

$$F_{t,T} = S_t e^{(r_{t,T} - q_{t,T})}$$

To derive the implied futures prices we use the Put - Call Parity relation, which must hold if arbitrage opportunities are to be avoided, independently of any option –pricing model:

$$c + Ke^{-r_{t,T}T} = p + F_{t,T}e^{-r_{t,T}T}$$

Where

c : The price of the ATM call option

K : The strike price of the options at time t, for maturity T

p : The price of the ATM put option

$F_{t,T}$: The Futures price at time t, for maturity T

To infer the Futures prices from the Put-Call Parity, reliable call and put option prices are required. We choose the closest to the money options for each day and for each maturity and we interpolate linearly between them to construct a synthetic ATM option and access its theoretical price. We use these options that are traded close to the money because they are the most actively traded and therefore the most liquid and most considered to be priced “fairly”.

After deriving the forward Index Level through the Put-Call Parity Relationship we have all the data required to use the Spot-Futures Parity. So we finally derive the implied dividend yields needed.

2.2 Screening the data

The raw data set is screened for the purposes of the subsequent analysis. The scope is to remove unreliable data from our database and keep only those that are considered reliable, meaning that they are less prone to be flawed by anomalies of the market such as mispricing; they do not provide opportunities arbitrage opportunities to be executed and they are not affected by microstructure concerns. The expiration date of each option contract is the third Friday of the expiration month.

The first step is to remove options with time to expiry less than five trading days. This is a standard practice in implied volatility indices calculation since options that are close to expiry are considered to be affected by liquidity and microstructure concerns. In the VIX index calculation for instance there is a roll over to the second and third shortest series contracts when the first – shortest series has less than eight calendar days to maturity. Unfortunately this possibility is not present in the case of the Greek market since ADEX introduces new options contracts only when the shortest series have expired. So, VASEX cannot be constructed for these days and this is a weakness of the constructed index.

We also discard options with zero trading volume and less than 3/8 premium.

The last step is to check whether the options that take part in the calculations violate the standard upper and lower arbitrage bounds. Given that the underlying asset of the FTSE/ASE-20 options, the FTSE/ASE-20 index, is a dividend paying asset we need to use the dividend yield as an input for the calculations. The implied dividend yield, calculated before following Ait-Sahalia and Lo (1998) method (the method is described before) is used for that scope. Options that violated these bounds were also discarded.

Section 3
Implied volatility index, construction and properties

3.1 VASEX Implied Volatility Index Construction

Following the standard practice in constructing implied volatility indices the Greek Implied Volatility Index VASEX represents the implied volatility of a synthetic at-the-money (ATM) option with 30 calendar days (22 trading days) to expiration.

We use the model-free methodology that CBOE uses to construct the VIX Index in order to construct the VASEX Index.

The Generalized formula used in the VASEX calculation is:

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

Where

σ is $VASEX/100 \Rightarrow VASEX = \sigma \times 100$

T : Time to expiration, in minutes

F : Forward Index level derived from index option prices

K_i : Strike Price of the *i-th* out-of-the-money option; a call if $K_i > F$ and put if $K_i < F$.

ΔK_i : The interval between strike prices – half the distance beween the strike on either side of *Ki* :

$$\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$$

K_0 : First strike below the forward index level, *F*

R : The risk-free interest rate to expiration

$Q(K_i)$: The closing price for each option with strike K_i

The options that take part in the above calculations are call and put options in the two nearest-term expiration months in order to bracket a 30-day calendar period. When the contract for the first expiration month is left with eight (8) days to expiration the CBOE in order to calculate the new VIX 'rolls' to the second and third contract months in order to minimize pricing anomalies that might occur close to expiration. However, for the case of the Greek market this is not possible since the ADEX does not provide option contracts for the third month until the first month contracts expire. So given this VASEX index was not calculated for the days where the first month contracts had less than five (5) trading days to expiration.

The time of the VASEX calculation is assumed to be 10:30 a.m. (Athens time). The model-free calculation of the volatility index measures the timi to expiration, T, in minutes rather than days in order to replicate the precision that is commonly used by professional traders. The time to expiration is given by the following expression:

$$T = \{M_{current\ day} + M_{settlement\ day} + M_{remaining\ day}\} \\ /Minutes\_in\_a\_year$$

Where…

$M_{current\ day}$ = Number of minutes remaining until midnight of the curent day

$M_{settlement\ day}$ = Number of minutes of minutes from midnight until 10:30 a.m. on the settlement day

$M_{remaining\ day}$ = Total number of minutes in the days between current day and the settlement day

Below we describe briefly the basic steps in the calculation of (1) :

<u>Step 1</u>

Determine the Forward Index Level, F, based on at-the-money option prices. The at-the-money strike is the strike price at which the difference between the all and put prices is the minimum.

The formula used to calculate the forward index level is the following:

$$F = Strike\ Price + e^{RT} \times (call\ price - put\ price)$$

Sort all of the options in ascending order by strike price. Select call options that have strike prices greater than *Ko* (OTM call options) and a **non-zero** price. After two consecutive calls with a price of zero are encountered, do not select any other calls. Select, also put options that have a strike prices less than *Ko* (OTM put options) and a non zero price. Again, after encountering two consecutive puts with a price of zero, do not select other puts. For the strike price *Ko* select both the call and put and average them to get a single value.

You should notice that two options are selected at *Ko* ,while a single option, either a call or a put, is used for every other strike price. This is done in order to center the strip of options around *Ko*. However, these two option prices are averaged so as to avoid double counting.

<u>Step 2</u>

Calculate the volatility for both near and next term options:

$$\sigma_1^2 = \frac{2}{T_1}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT_1} Q(K_i) - \frac{1}{T_1}\left[\frac{F_1}{K_0} - 1\right]^2 \qquad (1.1)$$

$$\sigma_2^2 = \frac{2}{T_2}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT_2} Q(K_i) - \frac{1}{T_2}\left[\frac{F_2}{K_0} - 1\right]^2 \qquad (1.2)$$

The constructed volatility index is an amalgam of the information reflected in the prices of all of the options used. The contribution of each option is proportional to its price (premium) and inversely proportional to its strike price.

Step 3

Finally we interpolate linearly between (1.1) and (1.2) to arrive at a single value with a constant maturity of 30 days to expiration. Then we get the square root of that value and we multiply it by 100 to get VASEX.

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

An important difference between our methodology and the CBOE's one is that the latter uses the midpoint of the bid-ask quote of options' prices for the calculations above. However, we use the closing prices of the ADEX options. As Skiadopoulos (2004) states "The option prices quoted as 'closing' in ADEX are not the last-traded prices. They are settlement prices in the sense that ADEX uses an algorithm to calculate them. For the shortest expiry, the three nearest-to-the-money call and puts are used. For the second expiry series only the closest-to-the-money call and put is required. Then, Black's (1976) model is used to back out the implied volatility using the last traded future price and a constant interest rate of 3%. In the next step, the arithmetic average of the implied volatility is obtained. Finally, the settlement option price is calculated using the average implied volatility and the future settlement price"

Moreover, Skiadopoulos (2004) constructed the GVIX index in two different ways; one using the closing prices and another one using the midpoint of the bid-ask quote of the options' prices and found that the volatility index constructed from bid–ask quotes is more prone to noise. Therefore the choice of the options' closing prices for the Greek case is justified.

3.2 Implementation Issues

The general formula (1) that CBOE uses to extract the implied volatility is a discretized version of the following formula (2), and is based on the concept of fair value of future variance developed by Demeterfi et al. (DDKZ variance). So, unlike the traditional ex-ante volatility measure such as the Black-Scholes-Merton implied volatility, the DDKZ variance is extracted directly from traded option prices.

$$V_{ddkz} = \frac{2}{T}\Big\{ rT - \left[\frac{S_0}{S_*}\exp(rT) - 1\right] - \ln\left(\frac{S_*}{S_0}\right)$$

$$+\exp(rT)\int_0^{S_*} \frac{P(T,K)}{K^2} dK$$

$$+\exp(rT)\int_0^{S_*} \frac{C(T,K)}{K^2} dK \qquad (2)$$

So it assumes that prices are available for options with any strike price between a given range $[K_{min}, K_{max}]$. This is not realistic as strike prices for trading in the market are listed only at a fixed increment. The limited availability of strike prices is present even in very developed derivatives market, such as the CBOE. To circumvent this problem Jiang and Tian (2005) proposed a method that they implemented in order to smooth the data set as if there were a much greater number of available strikes. We found that this technique would be very useful in our case. The Greek Derivatives Market counts only ten years of operations and is considered an emerging one. The availability of strike prices for the options traded in ADEX is indeed limited and the intervals between the strike prices is relatively high, so we applied the smoothing method that we describe below.

We reform the data set used in order to get a smoothed data set of option prices with a sufficiently large number of available strike prices. As far as options are listed for fixed strike prices the prices of the options with strike prices between any two listed strike prices are not directly observable. Hence, their prices must be inferred from the known prices of listed options. Toward this point, various approaches have been proposed. Among the approaches used in previous research, the curve-fitting method was found to be the most practical and effective one. Some studies have applied the curve-fitting method directly to option prices [e.g. Bates (1991)], but the nonlinear relationship between strike prices and option prices leads to numerical difficulties. Like Jiang and Tian that followed Shimko (1993) and Sahalia and Lo (1998), we apply the curve-fitting method to implied volatilities and not to option prices.

In particular, the curve-fitting method that is applied is the cubic spline interpolation. In the numerical analysis field, spline interpolation is a method of interpolation where the interpolant is a piecewise polynomial interpolation that is called spline. Among the different types of spline interpolation (i.e. Linear, Quadratic and Cubic spline interpolation) the cubic spline has the advantage that the obtained volatility function is smooth everywhere and provides an exact fit to the implied volatilities of the listed option prices that we can easily calculate.

In the first step prices of listed call and put options are translated into implied volatilities using the Black-Scholes-Merton (BSM) Model. Each parameter of the model is known, except for the dividend yield and the volatility, of course. The dividend yield used, is the implied one calculated before. Then a smooth function is fitted to the calculated implied volatilities (Volatility function). Given the known volatility function, we can extract then the implied volatilities for any strike price K_i. After having calculated the implied volatilities that needed, we use once more the BSM model, but this time in order to translate the extracted implied volatilities into call and put option prices.

In this stage we have to make clear that this curve-fitting method (cubic spline interpolation), does not make the assumption that the BSM model is the true model underlying the option prices. The results obtained (implied volatilities and option prices), should not be considered flawed due to the model used. The model is used just as a tool providing a one-to-one matching between option prices and implied volatilities.

3.3 Properties of the Greek implied volatility index, VASEX

After all these process were done VASEX could be eventually constructed for only 705 days for the period January 2004 to December 2008. In order to study the time series properties of the constructed index formally we proceed as follows. Table 1 shows the summary statistics (mean, median, maximum, minimum, standard deviation, skewness, kurtosis and the results from the Jarque-Bera test with its p-value in brackets) of the constructed implied volatility index and of the FTSE/ASE-20 index. It also presents the first order autocorrelation and the results from the Augmented Dickey-Fuller unit root test statistic. The highest level of VASEX is 53.12% and was reached on October 10, 2008 and the lowest level was 12.83% reached on November 14, 2005. The FTSE/ASE-20 Index reaches its highest level on November 11, 2007 and its lowest level on December 29, 2008 following, in the meanwhile, a downward trend. The mean of the VASEX is 20.37% and the median is 19.26%. We see that the skewness of the distribution is 2.69 implying a longer right tail and the kurtosis is 13.6, well above 3, showing that the distribution has fat tails. Regarding the autocorrelation coefficient the standard 5% significance bound is $2/\sqrt{T} = 2\sqrt{705} = 53.1$. The autocorrelations in the levels of the index are statistically significant and positive showing that it is a long-memory process. The conducted ADF test, including drift, for the existence or not of a unit root reject the existence of a unit root at 1% significance level whereas the results of the ADF test without including a drift for the process (-0.5842), suggests that there is a unit root at the same significance level (1%).

Figure 1 illustrates the evolution of VASEX along with the evolution of FTSE/ASE-20. As can be seen in certain periods there seems to be a negative correlation between the changes in the VASEX and the changes in the FTSE/ASE-20. This phenomenon has been termed as leverage effect [see Figlewski and Wang (2000)].

Table 2 shows the summary statistics, the first order autocorrelation and the results from the ADF test for the daily changes of the implied volatility index and the returns of the FTSE/ASE-20 index. The daily changes of the implied volatility index have a mean of zero indicating that there is no trend. The negative autocorrelation of the daily changes confirms what literature has proofed about an implied volatility index that is; ΔVASEX is a mean-reverting process. The implemented ADF test suggests the rejection of the null hypothesis of a unit root at 1% significance level.

Figure 2 illustrates the evolution of the changes in the levels of the VASEX index.

Statistics	*FTSE/ASE-20*	*VASEX*
Mean	1893,60	20,37
Median	1879,51	19,26
Standard Deviation	494,75	5,15
Minimum	887,92	12,83
Maximum	2841,23	53,12
Skewness	0,05	2,69
Kurtosis	1,84	13,60
J-B Stat	40,11*	4150,24*
p-value	0,001	0,001
ρ_1	0,9932*	0,9291*
ADF	-0,4481	-3,4597*

Table 1: Summary Statistics. The entries report the summary statistics for the levels of the stock index FTSE/ASE-20 and the implied volatility index VASEX. The first order autocorrelation $\rho 1$, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. An asterisk denotes rejection of the null hypothesis at the 1% level. The null hypothesis for the first order autocorrelation, Jarque-Bera and the ADF tests is that the first order autocorrelation is zero, that the series is normally distributed and that the series has a unit root, respectively. The sample spans the period January 2004 to December 2008.

Statistics	$R_{FTSE/ASE-20}$	*ΔVASEX*
Mean	-0,0004	0,0001
Median	0,0015	0,0003
Standard Deviation	0,0192	0,0192
Minimum	-0,1799	-0,1100
Maximum	0,0614	0,1022
Skewness	-2,4336	-0,3300
Kurtosis	19,2451	9,7822
J-B Stat	8436,059*	1362,0765*
p-value	0,001	0,001
ρ_1	0,0988*	-0,3392*
ADF	-16,4060*	-24,6452*

Table 2: Summary Statistics. The entries report the summary statistics for the daily first differences of the stock index FTSE/ASE-20 and the implied volatility index VASEX. The first order autocorrelation $\rho 1$, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. An asterisk denotes rejection of the null hypothesis at the 1% level. The null hypothesis for the first order autocorrelation, Jarque-Bera and the ADF tests is that the first order autocorrelation is zero, that the series is normally distributed and that the series has a unit root, respectively. The sample spans the period January 2004 to December 2008.

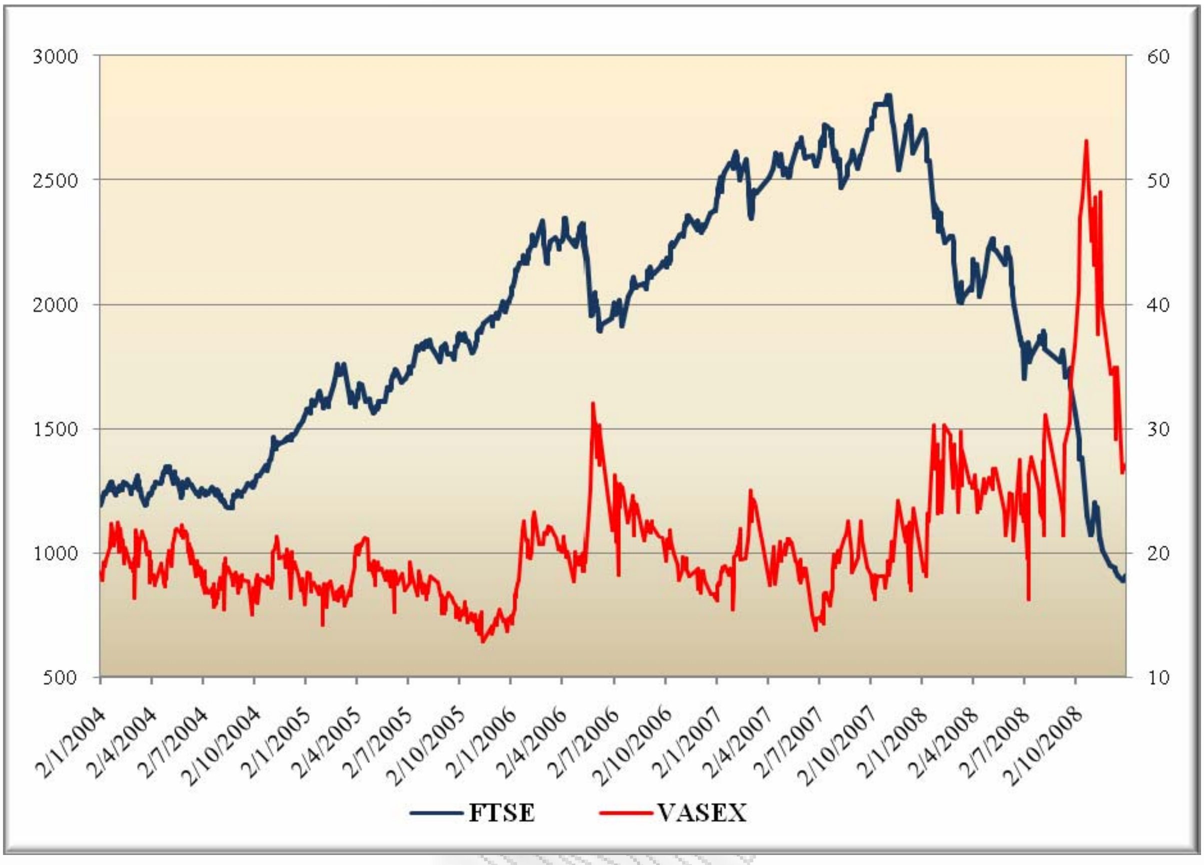

Figure (1): Evolution of FTSE/ASE-20 and VASEX. This figure illustrates the evolution of the FTSE/ASE-20 along with the evolution of VASEX for the period January 2004 to December 2008.

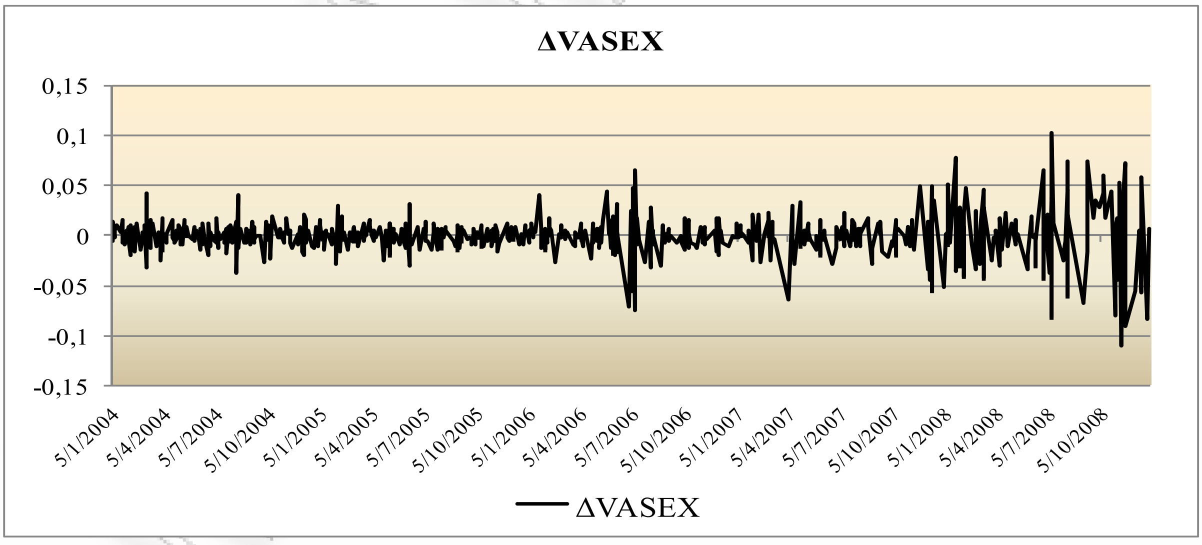

Figure (2): Evolution of ΔVASEX. This figure illustrates the evolution of the changes in the levels of VASEX (ΔVASEX) the data span the period January 2004 to December 2008.

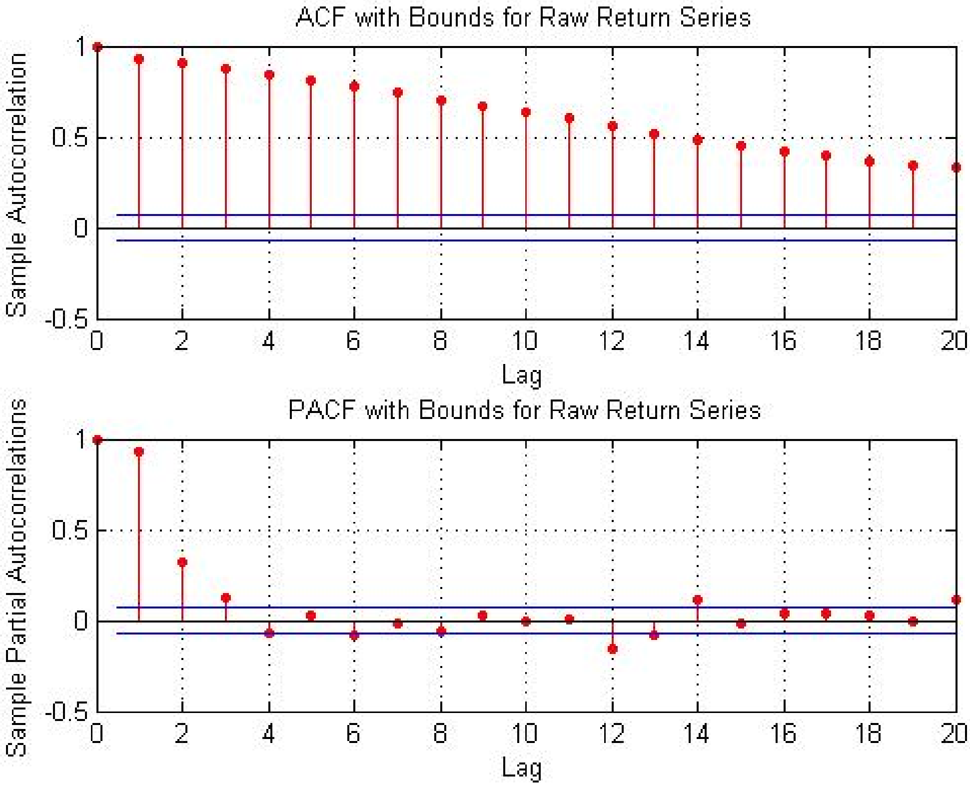

Figure (3): VASEX Autocorrelogram (up) and Partial-Autocorrelogram (down).

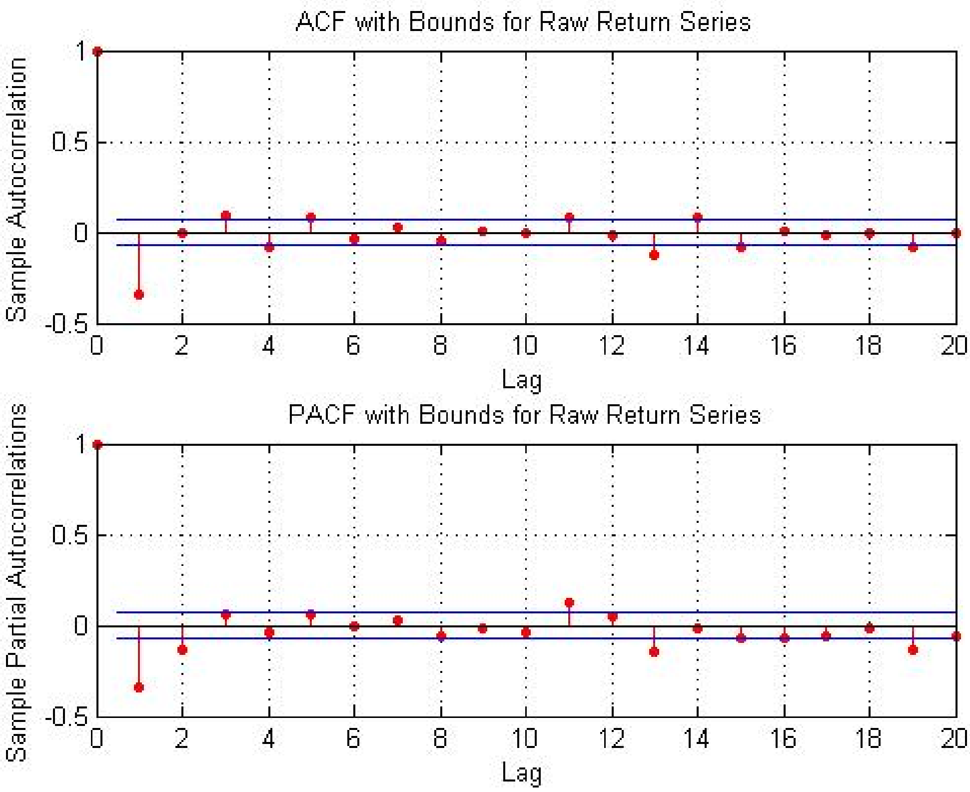

Figure (4): ΔVASEX Autocorrelogram (up) and Partial-Autocorrelogram (down).

Section 4
Relationship with the underlying stock index FTSE/ASE-20

In this section we examine the relationship between the Greek implied volatility index, VASEX and the underlying Greek stock index, FTSE/ASE-20. We first examine the leverage effect or the "Investor's fear gauge" property and then proceed with Granger causality tests in order to see whether the one index contains any information content, useful for the prediction of the other and vice – versa.

4.1 Investor's Fear Gauge - Leverage Effect

In the Capital Asset Pricing Framework is predicted that the expected return depends on the expected risk (expected volatility). Moreover, in the implied volatility literature the statistically significant negative relationship between implied volatility indices and returns is documented. For example Fleming et al (1995), Whaley (2000), Giot (2002a) and Carr and Wu (2006) have found a negative relationship between the returns of S%P stock index and the changes in VIX index. They also confirm that this relationship is asymmetric. Within the domestic implied volatility literature Skiadopoulos (2004) and Siriopoulos and Fassas (2008) also confirm this negative relationship between the returns of FTSE/ASE-20 and their constructed implied volatility indices.

The leverage effect states that when the stock price of a company falls, the company becomes more levered and riskier. This explanation of the increased volatility (associated with higher risk) that is applied to stocks is theoretical extended to stock indices as well. The explanation for the "leverage effect" has been called into question while several market anomalies have been associated with it. As Figlewski states, "A fall in the market price for the stock should increase its subsequent volatility, and a price rise off the same magnitude should reduce volatility by a comparable amount. However, the existence of a "leverage effect" is most commonly associated with falling, rather than rising, stock prices. This raises the question of whether it may be an asymmetrical phenomenon more closely related to negative returns than to leverage per se" [see Figlewski and Wang (2000)]. So, the conclusion is that the "leverage effect" is really a "down market effect".

An explanation that could be given is that when the market returns decline there is an increased demand for put options. As the demand increases the prices of the options increase and hence observe the presence of higher implied volatilities. Furthermore this negative relationship is asymmetric: a positive/negative shock on the implied volatility of equal size does not have the same effect on the return of the market index. That is where the interpretation of an implied volatility index as "the investor's fear gauge" lies on. The more the level of the implied volatility increases the more panic there is in the market. The more the level of the implied volatility decreases, the more complacency there is in the market.

To investigate whether this interpretation can be also attributed to VASEX we will execute the following regression.

$$R_t = c + b\Delta VASEX_t + \varepsilon_t \quad (4.1)$$

Where

$$R_t = ln(FTSE/ASE - 20_t / FTSE/ASE - 20_{t-1})$$

$$\Delta VASEX_t = VASEX_t - VASEX_{t-1}$$

The estimation output of the above regression is given below, in Table (3)

	Dependent Variable: R_t		
	Independent Variables		***Adj. R^2***
	Intercept	*ΔVASEX*	
Coeff.	-0,00	-0,16*	**0,025**
t-stat.	(-0,44)	(-2,11)	

Table (3): Results of the regression $R_t = c + b\Delta VASEX_t + \varepsilon_t$. Reported values are the estimated coefficients of the regression, where $\Delta VASEX_t$ denotes the changes and the of the implied volatility index and R_t the returns of the underlying stock index at time t. Heteroskedasticity and autocorrelation consistent Newey-West standard errors were estimated and the corrected t-values are reported. One asterisk denotes the rejection of the null hypothesis of a zero coefficient at 5% significance level.

Because of the existence of autocorrelation and heteroskedasticity in the residuals of the above regression we use autocorrelation and heteroskedasticity consistent Newey-West standard errors which do not cause any change in the estimated coefficient values but the standard errors and correspondingly the estimated t-values. The estimated beta coefficient of the ΔVASEX is statistically significant in a 5% significance level and its negative sign implies that there is a negative relation between the returns of the FTSE/ASE-20 index and the changes in the levels of implied volatility. The interpretation of the negative coefficient of VASEX in the regression is that if VASEX falls by 100 basis points (1%) the return of FTSE/ASE-20 will rise by 0.162%, whereas if VASEX rise by 100 basis points (1%) the return of FTSE/ASE-20 will fall by 0.162%.

In order to estimate whether this negative relationship is asymmetric we follow Whaley's (2000) and Skiadopoulos (2004) methodology in that we regress the logarithmic daily returns R_t of the FTSE/ASE-20 stock index on the daily changes Δ of VASEX and on the positive changes $\Delta VASEX^+$ of VASEX as a second regressor.

So, $\Delta VASEX^+ = \Delta VASEX$ if $\Delta VASEX > 0$ and $\Delta VASEX^+ = 0$, otherwise.

The regression is expressed as:

$$R_t = c + b_1 \Delta VASEX_t + b_1 \Delta VASEX_t{}^+ + \varepsilon_t \tag{4.2}$$

The estimation output is given below:

Dependent Variable: R $_t$				
	Independent Variables			***Adj. R*** ^{2}
	Intercept	ΔVASEX	$\Delta VASEX^+$	
Coeff.	0,00	0,17***	-0,70*	**0,099**
t-stat.	(4,23)	(1,85)	(-3,51)	

Table (4): Test for the existence of an asymmetric leverage effect. Reported values are the estimated coefficients of the regression $R_t = c + \Delta VASEX_t + \Delta VASEX_t^+ + \varepsilon_t$, where $\Delta VASEX_t$ and $\Delta VASEX_t^+$ denote the changes and the positive changes respectively of the implied volatility index and R_t the returns of the underlying stock index at time t. Heteroskedasticity and autocorrelation consistent Newey-West standard errors were estimated and the corrected t-values are reported. One and three asterisks denote the rejection of the null hypothesis of a zero coefficient at 1% and 10% significance level respectively.

The coefficient of $\Delta VASEX_t$ is statistically significant at the relatively low significance level of 10%. The coefficient of $\Delta VASEX_t^+$ is statistically significant at 1% significance level. These results suggest that through the estimation period, the positive changes of ΔVASEX are the ones that mainly affect the return of the FTSE/ASE-20. Curiously, the estimated coefficient of $\Delta VASEX_t$ is positive, indicating that whatever the evolution of the implied volatility is the return of the FTSE/ASE-20 index will fall. In the cases where $\Delta VASEX_t$ is positive ($\Delta VASEX_t > 0$) the fall of the FTSE/ASE-20 return will be greater. More specifically, we see that if VASEX falls by 100 basis points (1%) the return of FTSE/ASE-20 will fall by 0.17%, whereas if VASEX rises by 100 basis points (1%) the return of FTSE/ASE-20 will have a greater fall of 0.53%. This is indeed weird, given that we have ensured from the previous test [equation (4.1)], that the relation between ΔVASEX and FTSE/ASE- 20 returns is negative.

The only possible explanation for this disturbance is the impact of the global financial crisis of 2008. The index was constructed for the time period January 2004 to December 2008. The period from the beginning of 2004 up to almost October 2007, excluding a slight downward trend in 2006 for two consecutive months (April to June) was an extremely positive one for the returns of the Athens Stock Exchange. However, from October 2007 to December 2008 (end of our sample) the FTSE/ASE-20 index follows an intense downward trend, making only little corrections. In fact, this downward trend is driven by the global credit crisis that we are still going through. The fact that the stock index returns are falling almost continuously for a so long time period in our sample maybe explains why we got these strange results.

4.2 Impact of the 2008 Global Financial Crisis

To see whether the global financial (credit) crisis has an effect on the volatility and the stock returns of the Greek market and confirm our relative thoughts we proceed in running a third regression. In this case, we add two new regressors for the variables $\Delta VASEX_t$ and $\Delta VASEX_t^+$, including a multiplicative dummy variable D in the regression model of equation (4.2), that is:

$$R_t = c + a_1 \Delta VASEX_t + a_2 \Delta VASEX_t^+ + b_1 D \Delta VASEX_t + b_2 D \Delta VASEX_t^+ + \varepsilon_t \quad (4.3)$$

Where $D = 1$, if $t > 1/1/2008$ and $D = 0$, otherwise. The beginning of the global financial crisis dates back to the last months of the year 2007. It was then, that the international stock exchanges began to get hailed by severe losses. For this reason, in this study we set the whole year 2008 as a period of financial turmoil. The estimated output is given in table (5).

As we see, the coefficients b_1 and b_2 are statistically significant and different from zero. Moreover we see that the coefficient b_1 is positive, implying that whatever the changes of the implied volatility index were during the prolonged period of the Athens Stock Exchange downturn, the return of the FTSE/ASE-20 index was negative. So we can claim that the prolonged fall of the returns of the Athens Stock Exchange, driven mainly by the global credit crisis, is the source of the disturbance on the risk-return relationship.

Dependent Variable: R_t						
	Independent Variables					***Adj. R^2***
	Intercept	ΔVASEX	$ΔVASEX^+$	DΔVASEX	DVASEX+	
Coeff.	0,00*	-0,12***	-0,15	0,41*	-0,76*	**0,127**
t-stat.	(2,78)	(-1,69)	(-0,96)	(3,69)	(-2,89)	

Table (5): Testing for the impact of the global financial crisis of 2008 on the risk-return relationship of the Greek market. Reported values are the estimated coefficients of the regression $R_t = c + \alpha_1 \Delta VASEXt + \alpha_2 \Delta VASEX_t^+ + b_1 D\Delta VASEX_t + b_2 D\Delta VASEX_t^+ + \varepsilon_t$. Heteroskedasticity and autocorrelation consistent Newey-West standard errors were estimated and the corrected t-values are reported. One, two and three asterisks denote the rejection of the null hypothesis of a zero coefficient at 1%, 5% and 10% significance level respectively.

It should be noted that in order to test the robustness of these results we run the regression, expressed in equation (4.2) using two sub-samples. One for the period before the crisis; which is January 2004 to December 2007 and one for the period January 2008 to December 2008. The results from these tests confirm the above conclusions.

4.3 Granger Causality Test

A time series X is said to Granger-cause a time series Y if X helps in the prediction of Y, or equivalently if the coefficients of the lagged X's statistically significant. When dealing with Granger causality it is important to note that the statement "X Granger causes Y" is not implying that Y is the effect or the result of X. This kind of causality measures precedence and information content but it does not by itself indicate causality in the more common use of the term (see Hamilton, 1994, for a more detailed description of the Granger Causality Test).

In this section we perform a Granger Causality test in order to check whether ΔVASEX (R) helps to predict R (ΔVASEX). At this point we should note that in order to have robust results for the predictive power of variables we must have observations of a certain and fixed frequency. We should mention that VASEX could be constructed for very few days for the last months of the year 2008 due to the liquidity drought of the Athens Derivatives market; options contracts with traded volume different from zero were hardly recognized in most days, for the second shortest options contracts series. So, while up to July 2008 we have a sufficient number of observations to regard them as daily, for the last months of the year we have about thirty observations. This means that the changes of the implied volatility index (and the returns of the FTSE/ASE-20 index) for this time period would be more like weekly rather than daily. To avoid having flawed results in the test we rearrange our sample and include every observation within the time period January 2004 – July 2008 (including this month).

The Granger causality test consists of running bivariate regressions of the form:

$$\Delta VASEX_t = c + \sum_{i=1}^{K} a_i \Delta VASEX_{t-i} + \sum_{i=1}^{K} b_i R_{t-i} + \varepsilon_t \qquad (4.4)$$

$$R_t = c + \sum_{i=1}^{K} a_i R_{t-i} + \sum_{i=1}^{K} b_i \Delta VASEX_{t-i} + \varepsilon_t \qquad (4.5)$$

The null hypothesis is $H_0 : b_1 = b_2 = \dots = b_K = 0.$

Or put it differently, we test two hypotheses, namely that "R does not Granger-cause ΔVASEX" and that "ΔVASEX does not Granger-cause R".

The test for causality is based on an F-statistic that is calculated by estimating the above expressions in both unconstrained and constrained forms. The unconstrained forms are the above expressions (regressions) themselves whereas the constrained forms are the above regressions without the terms of the sum of the lagged values of the other variable or put it more simply, just the autoregressive regressions for each variable with the same lag length (K) used before. According to Hamilton (1994) a time series X fail to predict - does not Granger-causes – a time series Y if the Mean square error (MSE) of the unconstrained regression is the same as the MSE of the constrained regression.

The interpretation of the null hypothesis is that R does not Granger-causes ΔVASEX in the first regression and that ΔVASEX does not Granger-causes R in the second regression.

We execute the test two times, using one lag (K = 1) in the first test and two lags (K = 2) in the second test.

Table (6) shows the results (F-statistics) of the Granger causality test and Table (7) shows the estimated coefficients along with the corresponding t-values and the adjusted R^2 of the regressions.

Let us have a look at the results of the Granger causality test using 1 lag first. We see that ΔVASEX Granger-causes R for a significance level of 5%. The adjusted R^2 of the regression is just 0.005. This number is too small and we do not really expect that the information content of ΔVASEX to be really helpful in R's prediction. The opposite is also true, meaning that R Granger causes ΔVASEX. The adjusted R^2 of this regression is 0.1799. This number is sufficiently high to claim that R really helps predict ΔVASEX. Now, let us see the results of the test using 2 lags. Once again both variables Granger-cause each other with the adjusted R^2 lying on the same levels. These results are in line with Siriopoulos and Fassas (2008). Hence, the results provide us one important finding; the power of lagged values of R to help predict the changes in the levels of implied volatility. Consequently the future option prices can be forecasted and provide a tool for following the appropriate in each case strategy.

Granger Causality for $R_{FTSE/ASE-20}$ and $\Delta VASEX$				
Null Hypothesis:	1 lag		2 lags	
	F-Stat.	Prob.	F-Stat.	Prob.
$R_{FTSE/ASE-20}$ does not Granger Causes $\Delta VASEX$	4,80*	0,029	4,15*	0,016
$\Delta VASEX$ does not Granger Causes $R_{FTSE/ASE-20}$	5,36*	0,021	3,20*	0,041

Table (6): Results from the Granger causality test between R and ΔVASEX. The results refer to the the equations (4.4) and (4.5). We use both 1 and 2 lags. The data spans the period January 2004 to July 2008. One asterisk denotes the rejection of the null hypothesis at the 5% significance level.

Dependent Variable: R_t						
						1 lag (K = 1)
	Independent Variables					***Adj. R^2***
	Intercept	R_{t-1}	R_{t-2}	$\Delta VASEX_{t-1}$	$\Delta VASEX_{t-2}$	
Coeff.	0,00	0,02	–	0,09*	–	0,51%
t-stat.	(1,03)	(0,52)	–	(2,31)	–	
						2 lags (K = 2)
Coeff.	0,00	0,02	0,02	0,07***	-0,04	0,42%
t-stat.	(0,98)	(0,50)	(0,39)	(1,67)	(-1,02)	
Dependent Variable: $\Delta VASEX_t$						
						1 lag (K = 1)
	Independent Variables					***Adj. R^2***
	Intercept	$\Delta VASEX_{t-1}$	$\Delta VASEX_{t-2}$	R_{t-1}	R_{t-2}	
Coeff.	0,00	-0,44*	–	-0,08**	–	17,99%
t-stat.	(0,32)	(-12,11)	–	(-2,19)	–	
						2 lags (K = 2)
Coeff.	0,00	-0,50*	-0,15*	-0,08**	-0,07***	19,67%
t-stat.	(0,41)	(-12,69)	(-3,82)	(-2,20)	(-1,85)	

Table (7): Granger causality tests between ΔVASEX and R. Results from the equations (4.4) and (4.5). The top panel refers to the test using 1 lag (K=1). The bottom panel refers to the test using 2 lags (K=2). The reported values are the estimated coefficients of the bivariate regressions and refer to the lagged values of ΔVASEX and the lagged values of R, at time t. T-values, R^2 and adjusted R^2 are also reported. One, two and three asterisks denote the rejection of the null hypothesis of a zero coefficient at 1%, 5% and 10% significance level respectively.

4.4 Is the Greek Implied Volatility Index, VASEX a Leading-Market Indicator?

The contemporaneous negative relationship between implied volatility indices and the returns of the underlying stock indices is well documented by empirical results. It also holds for the Greek Implied volatility index (VASEX), as we reported previously. What is unclear though is whether implied volatility indices can indicate overbought or oversold market conditions and thus provide trading signals.

This is a question that arises from the fact that when implied volatility indices reach very high levels the underlying stock indices usually their very low levels. Therefore, the ability of an implied volatility index to provide a market-timing tool to the investors is under research.

Giot (2005b) examines whether the VIX and VXN indices can indicate if the condition of the U.S. market is overbought or oversold and thus provide trading signals. He reports that there is some evidence that one can expect positive forward-looking returns for long positions in the stock indices when the implied volatility indices reach high levels. However, he reports that one can wait for extremely high levels of implied volatility to obtain really attractive forward-looking returns.

In this subsection we examine the relationship of the Greek implied volatility index (VASEX) with the forward-looking returns of the underlying stock index (FTSE/ASE-20).

In line with Giot, we study the relationship between the level of the Greek implied volatility index, VASEX, at a given time and the forward-looking (logarithmic) return of the FTSE/ASE-20 index for one (1), five (5), twenty (20) and sixty (60) days ahead. Hence, we look at the relationship between $VASEX_t$ and $r1d_t$, $r5d_t$, $r20d_t$ and $r60d_t$.

To examine whether extremely high implied volatility levels provide signals to an investor to take long positions on the underlying stock index we use the following process to determine our trading strategy:

<u>Step 1:</u>

At any given time t, we observe the T previous (historical) values of the implied volatility index, that is a set $\{VASEX_i\}$, where $i \in [t-T, t-1]$. We set T to be equal to one-hundred (T = 100), so we study the 100 previous values of the implied volatility. These implied volatility levels are classified according to twenty (20) equally spaced percentiles, i.e. *5%, 10%, 15%…95%*. These percentiles refer to a state for the implied volatility and are denoted as $S_1, S_2 \dots S_{20}$.

The set of the T values is the specification of our information set for each time t. We use a rolling window procedure for the determination of our information sets that is, each day we move one observation forward.

Step 2:

The implied volatility of each day, $VASEX_t$, is compared with these percentiles and gets the corresponding rank. If $VASEX_t$ happens to be greater than the maximum of the its previous values, then it is classified with a rank $S_t = 21$.

Step 3:

Given the state of each t, for each day we compute the forward looking returns on the FTSE/ASE-20 stock index. The periods taken into consideration for the computation of these returns are 1 day, 5 days, 20 days and 60 days.

If implied volatility is capable of providing trading signals for long positions on the stock index, then we should wait that the returns for these positions in the high-volatility states should be sufficiently large. Table (8) reports the values and the standard deviations of the returns on our strategy for each one of the 21 volatility states. The results show that there is a clear increase, with some significant in some cases fluctuations though, in the level of risk that an investor faces as we move from low to high volatility states. As for the returns, we see that there is not a clear pattern, at least for the middle states. However, we observe something really interesting. Contrasts to our beliefs, the forward-looking returns on the very low volatility periods are always positive while the forward-looking returns on the very high volatility regimes are always positive. This fact does not comply with what traders think about the signals contained in the spikes of implied volatility. What is also interesting to refer is that the increasing risk that we observe is not accompanied with higher returns as investors would expect.

	Forward-Looking Horizon							
	1 *Day*		**5 *Days***		**20 *Days***		**60 *Days***	
State (S)	R	St. Dev	R	St. Dev	R	St. Dev	R	St. Dev
S1	0,03	0,82	0,74	2,13	1,83	4,20	8,10	6,64
S2	0,12	0,83	0,59	2,05	1,51	5,06	6,50	6,89
S3	-0,01	0,85	-0,03	2,06	-0,10	4,10	4,18	6,06
S4	0,12	1,02	0,15	2,31	2,09	4,92	4,26	10,30
S5	-0,03	1,37	-0,04	3,41	0,27	7,94	-0,89	19,32
S6	0,02	0,81	-0,03	2,96	0,78	5,58	1,09	16,11
S7	0,12	0,95	0,42	3,51	1,36	6,16	3,01	16,72
S8	0,12	1,01	-0,73	3,13	0,45	5,94	-1,14	17,26
S9	-0,06	1,01	-0,19	2,75	0,03	6,85	3,83	9,86
S10	-0,03	1,64	-0,51	3,11	0,55	6,78	-4,35	16,55
S11	-0,31	1,03	-0,06	2,73	-0,87	6,93	0,22	18,39
S12	-0,02	1,18	-1,36	3,84	-0,71	7,72	2,96	9,70
S13	0,41	1,30	0,47	3,66	-2,69	9,26	0,63	11,96
S14	-0,46	1,05	-0,39	3,73	-1,69	9,12	-2,52	17,68
S15	-0,27	1,16	0,68	2,69	3,52	3,10	4,36	12,53
S16	0,28	1,15	0,17	3,27	2,25	4,96	0,98	13,52
S17	0,19	1,62	0,30	2,95	2,76	3,16	-1,53	12,72
S18	0,26	1,20	-1,06	3,23	0,06	4,06	-9,05	16,60
S19	-0,55	2,47	-1,19	5,12	-3,52	8,56	-5,34	15,22
S20	-0,66	2,25	-1,64	4,72	-5,03	9,28	-7,38	16,08
S21	-0,47	3,04	-3,34	6,03	-9,24	13,39	-15,88	24,53

Table (8): Results of the trading strategy for the FTSE/ASE-20 index. In columns 2 to 9 are reported respectively the average and standard deviation of the 1-, 5-, 20- and 60-day forward looking returns which belong to state *S* (first column). The time period is July 2004 - March 2009.

To set the above analysis in an econometrics framework we will use the following regressions, used also by Giot (2005b):

$$r1d_t = \beta_1 D1_t + \beta_2 D2_t + \cdots + \beta_{21} D21_t + \varepsilon_t \tag{4.6}$$

$$r5d_t = \beta_1 D1_t + \beta_2 D2_t + \cdots + \beta_{21} D21_t + \varepsilon_t \tag{4.7}$$

$$r20d_t = \beta_1 D1_t + \beta_2 D2_t + \cdots + \beta_{21} D21_t + \varepsilon_t \tag{4.8}$$

$$r60d_t = \beta_1 D1_t + \beta_2 D2_t + \cdots + \beta_{21} D21_t + \varepsilon_t \tag{4.9}$$

Where

$D1_t$, $D2_t$, …, $D21_t$ are dummy variables defined such that $Di_t = 1$ if $S_t = i$ and $Di_t = 0$ elsewhere. Each coefficient β_i stands for the forward-looking return on the FTSE/ASE-20 at time *t* and over the given time horizon when $GVIX_t$ is classified into the state S_t .

The estimation output is given below in table (9). The estimated t-statistics of the coefficients are computed using Newey-West autocorrelation and heteroskedasticity consistent standard errors, as the periods for which we compute the forward-looking returns are by construction overlapping. The estimated coefficients, which stand for the returns are the same as before, in table (8), but now we can infer whether or not they are statistically significant. We see that in general the returns for the middle categories are not statistically significant except for the categories D13 and D14 for the 1 - day forward-looking return. For the 5 -, 20 - and 60 - days forward-looking returns in the very low volatility state S_1, the coefficients of the dummy variable D1 are all statistically significant and positive. For the very high volatility states D19, D20 and D21 the coefficients are all negative and some of them statistically significant. Thus, our previous conclusions about the not favorable risk-return relationship are confirmed. A possible explanation for the results that we get comes easily as we think about the circumstances during the time period that we study. The years 2004 to 2007 where extremely favorable for the investors as on the one hand the stock returns were sufficiently high and on the other hand, the volatility of the stock market was relatively low. However from the late months of 2007 until December 2008 that is the terminal month of our sample everything earned in all of these years was vanished due to the global financial crisis, with the volatility of the market reaching very high levels. So, it is not weird that the higher returns we observe happen to occur in the very low volatility regimes. We can say that since VASEX cannot provide profitable trading signals is not a market-leading indicator.

Forward-Looking Horizon				
Dummy Variable	$r1d$	$r5d$	$r20d$	$r60d$
D1	0,03 (0,32)	0,74** (2,13)	1,83** (2,10)	8,10* (6,32)
D2	0,12 (0,81)	0,59 (1,51)	1,51 (1,41)	6,50* (4,62)
D3	-0,01 (-0,08)	-0,03 (-0,06)	-0,10 (-0,11)	4,18* (3,15)
D4	0,12 (0,74)	0,15 (0,33)	2,09*** (1,95)	4,26** (1,98)
D5	-0,03 (-0,10)	-0,04 (-0,05)	0,27 (0,14)	-0,89 (-0,20)
D6	0,02 (0,11)	-0,03 (-0,05)	0,78 (0,56)	1,09 (0,29)
D7	0,12 (0,73)	0,42 (0,62)	1,36 (1,05)	3,01 (0,82)
D8	0,12 (0,56)	-0,73 (-1,05)	0,45 (0,33)	-1,14 (-0,28)
D9	-0,06 (-0,28)	-0,19 (-0,29)	0,03 (0,02)	3,83 (1,61)
D10	-0,03 (-0,12)	-0,51 (-0,80)	0,55 (0,38)	-4,35 (-1,28)
D11	-0,31 (-1,16)	-0,06 (-0,09)	-0,87 (-0,49)	0,22 (0,05)
D12	-0,02 (-0,09)	-1,36 (-1,54)	-0,71 (-0,33)	2,96 (1,21)
D13	0,41*** (1,74)	0,47 (0,58)	-2,69 (-1,19)	0,63 (0,22)
D14	-0,46** (-2,04)	-0,39 (-0,43)	-1,69 (-0,64)	-2,52 (-0,52)
D15	-0,27 (-1,29)	0,68 (1,39)	3,52* (5,89)	4,36 (1,13)
D16	0,28 (1,52)	0,17 (0,22)	2,25** (2,09)	0,98 (0,26)
D17	0,19 (0,65)	0,30 (0,51)	2,76* (3,98)	-1,53 (-0,49)
D18	0,26 (1,15)	-1,06 (-1,63)	0,06 (0,07)	-9,05** (-2,26)
D19	-0,55 (-1,60)	-1,19 (-1,20)	-3,52*** (-1,76)	-5,34 (-1,56)
D20	-0,66 (-1,64)	-1,64*** (-1,69)	-5,03** (-2,50)	-7,38** (-2,25)
D21	-0,47 (-0,64)	-3,39 (-1,44)	-9,24*** (-1,68)	-15,88 (-1,52)

Table (9): Regression results for the trading strategies of equations (4.6), (4.7), (4.8) and (4.9) for the FTSE/ASE-20 index. Each column gives the estimated coefficient for the dummy variable listed in the first column, respectively for the 1-, 5-, 20- and 60-day forward-looking returns. Newey-West t-statistics are given in parenthesis. The time period is July 2004 - March 2009.

Section 5
Relationship with international markets

In this section we examine the relationship of the Greek implied volatility index with other implied volatility indices. More specifically, we investigate whether there are any transmission effects of the implied volatility across several markets. More specifically we examine the transmission of volatility across the CBOE's VIX index, the Deutsche Börse's VDAX index, the Paris Bourse's VCAC index, the SIX Swiss Exchange's VSMI index, the European VSTOXX index and the Greek VASEX index.

5.1 Evolution and Summary statistics of the implied volatility indices

The data for the closing prices of the above indices were downloaded from DataStream and Bloomberg. Figure (5) shows the evolution of these six indices over the period January 2004 – December 2008.

We can observe that the indices are moving together in certain time periods and that is why we expect that the indices are correlated up to some degree. As we can see VASEX is generally moving in higher levels than the other indices. That was expected as the spread among the implied volatility indices can be seen as the different level of riskiness among the countries – markets to which they refer. The Greek market is indeed riskier than the other markets taken into account in this study.

Table (10) presents the summary statistics of the above indices and their daily changes ($\Delta Index_t = Index_t - Index_{t-1}$) as well as the first order autocorrelation and the results from the ADF unit root test statistic. Figure () plots each implied volatility index separately, in order to have a clear demonstration of each one's evolution through the period studied.

The Jarque-Bera test values imply that none of the implied volatility indices is distributed normally either in the levels or in the first differences. In addition, most indices exhibit strong autocorrelation both in the levels and in their first differences. Finally, the values of the ADF test show that implied volatility indices are non-stationary in the levels except for VDAX and VCAC where we can reject the null hypothesis of the existence of a unit root at a 5% significance level, but they are all stationary in their first differences.

Once again for the reasons mentioned before we will use for the scope of analysis the rearranged sample that covers the period January 2004 – July 2008 (including July). At this point we should note that due to time zone differences the data is synchronized as far as it concerns the same calendar day.

Evolution of the Implied Volatility Indices over the period January 2004 – December 2008

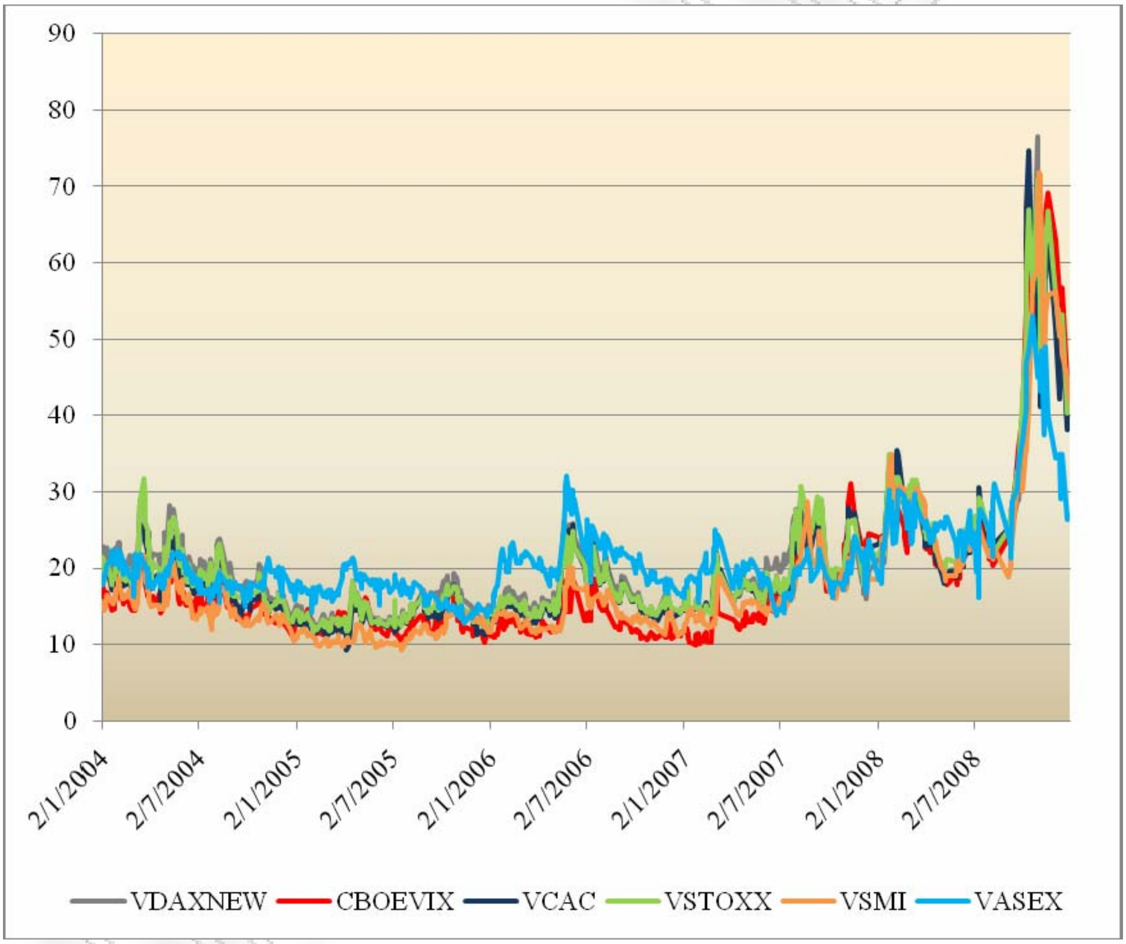

Figure (5): The figure shows the daily evolution of the implied volatility indices over the period January 2004 to December 2008. The data set used for the construction of the figure was synchronized to deal with the days in which VASEX was calculated.

Panel A: Summary statistics for the levels of the implied volatility indices					
	VIX	*VDAX*	*VCAC*	*VSMI*	*VSTOXX*
Mean	18,23	20,77	19,79	17,92	20,57
Median	14,80	18,49	17,28	14,83	17,81
St. Deviation	10,75	9,74	9,39	9,70	10,12
Minimum	9,89	11,65	9,24	9,24	11,60
Maximum	80,86	83,23	78,05	84,90	87,51
Skewness	3,13	3,33	3,03	3,06	3,15
Kurtosis	13,84	16,18	14,19	14,21	14,64
J-B Stat	8513,31*	11856,83*	8638,76*	8586,01*	9313,20*
p-value	0,0010	0,0010	0,0010	0,0010	0,0010
ρ_1	0,984*	0,984*	0,976*	0,988*	0,981*
ADF	-2,3178	-2,9581**	-3,2853**	-2,7124	-2,7552

Panel B: Summary statistics for the daily changes in the implied volatility indices					
	ΔVIX	*ΔVDAX*	*ΔVCAC*	*ΔVSMI*	*ΔVSTOXX*
Mean	0,00	0,00	0,00	0,00	0,00
Median	0,00	0,00	0,00	0,00	0,00
St. Deviation	0,02	0,02	0,02	0,01	0,02
Minimum	-0,17	-0,15	-0,21	-0,16	-0,14
Maximum	0,17	0,22	0,28	0,16	0,23
Skewness	0,28	2,08	1,04	0,33	2,55
Kurtosis	28,86	43,74	54,19	47,01	45,65
J-B Stat	36339,10*	91139,34*	139903,37*	101955,66*	97995,18*
p-value	0,001	0,001	0,001	0,001	0,001
ρ_1	-0,132*	0.086*	-0,103*	0,183*	-0,0382*
ADF	-31,6336*	-25,0945*	-29,4664*	-25,1197*	-27,9112*

Table (10): Summary Statistics. The entries report the summary statistics for each of the implied volatility indices in the levels and the daily first differences. The first order autocorrelation $\rho 1$, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The null hypothesis for the first order autocorrelation, Jarque-Bera and the ADF tests is that the first order autocorrelation is zero, that the series is normally distributed and that the series has a unit root, respectively. The sample spans the period January 2004 to December 2008.

5.2 Correlation Analysis

In order to have a first feeling of the relationship among the implied volatility indices under examination we have a look on their first order cross – correlations. Table (11) provides the correlation coefficients.

	ΔVASEX	*ΔVIX*	*ΔVDAX*	*ΔVCAC*	*ΔVSTOXX*	*ΔVSMI*
ΔVASEX	1,00	0,15	0,27	0,26	0,27	0,15
ΔVIX	0,15	1,00	0,63	0,62	0,65	0,15
ΔVDAX	0,27	0,63	1,00	0,89	0,94	0,26
ΔVCAC	0,26	0,62	0,89	1,00	0,90	0,22
ΔVSTOXX	0,27	0,65	0,94	0,90	1,00	0,28
ΔVSMI	0,15	0,15	0,26	0,22	0,28	1,00

Table (11): Cross-correlations between the changes in the levels of implied volatility indices. The data used in the estimation of the correlation coefficients span the period January 2004 to July 2008.

As we can see the changes in the levels of the implied volatility indices are correlated up to a significant degree. ΔVASEX is most highly correlated with the changes of VSTOXX, VDAX and VCAC (ΔVSTOXX, ΔVDAX and ΔVCAC respectively) not ignoring however the correlations with the other indices. What we also see is that VIX, VDAX and VSTOXX are the indices that play the major role in transmitting the implied volatility levels. For a more formal and robust analysis we proceed the analysis, using the econometric methodology described below.

5.3 Econometric Methodology

In order to examine the spillovers of the implied volatility among the markets, a Vector Autoregressive model (VAR) and the Granger causality tests were used. These tests were executed for the time series of the changes of the implied volatility indices rather than the levels. The reason behind that is that the changes of the indices are all stationary and moreover they do not contain any idiosyncratic risks (i.e. country risk and political risk). Moreover, as Poon and Granger (2003) show, implied volatility does not stand for an unbiased measure of realized future volatility and using the changes in the levels of implied volatility reduces this bias. In addition, as Aboura and Villa (1999) mention it makes more sense to assume that the changes in the level of the implied volatility indices lead to changes in the levels of the other implied volatility indices.

5.3.1 VAR Analysis

Vector autoregressions models have become popular through the work of Sims (1980) and they have been used extensively for analyzing the dynamics of macroeconomic systems. VAR models are widely used to capture the dynamic structure of interrelated time series. The main question addressed by VARs is the effect of a shock in a variable and its effect on the other variables of the system. The main advantage of VAR models is that they allow us to study jointly multiple time series and find the correlations between the disturbances across equations. On the other hand, in a single equations framework the impact of random disturbances on the system would be ignored. The VAR modeling framework has been employed in a number of studies to investigate the transmission of implied volatility across international markets. Evidence for the volatility spillover have been found i.e. by Gemmill and Kamiyama (2000), Aboura (2003), Nikkinen and Sahlström (2004c), Skiadopoulos (2004), Nikkinen et al. (2006), Siriopoulos and Fassas (2008), Äijö (2008b) and Badshah (2009).

A VAR model analyzes each endogenous variable as a function of the lagged values of every other endogenous variable in the VAR system. The mathematical expression of the used standard VAR (1) model is:

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + \varepsilon_t$$

Where

$\Delta IV_t = IV_t - IV_{t-1}$ is the (6×1) vector of changes in the implied volatility indices between *t*-1 and *t*, C is a (6 x 1) vector of constants, Φ is a (6 x 6) matrix of coefficients and ε_t is a (6 x 1) vector of residuals.

To build the model we first define the endogenous variables, which is the matrix ΔIV_t.

$$\Delta IV_t = [\ \Delta VASEX_t \quad \Delta VIX_t \quad \Delta VDAX_t \quad \Delta VCAC_t \quad \Delta VSTOXX_t \quad \Delta VSMI_t\ ]'$$

The set of the exogenous variables included in the model is a (6×1) vector of constants.

We will proceed in the analysis using a VAR (1) model. In order to avoid the over fitting of the employed model, the number of lags was chosen so as to minimize the Schwartz's Bayesian Criterion (BIC) and to keep the model parsimonious. The VAR model will be estimated on a common sample of implied volatility indices. This common sample spans the period January 2004 to July 2008. After synchronization of the data, the total numbers of observations used for the VAR estimation are 672.

Table (12) shows the estimated coefficients, the t-statistics and the adjusted R^2 for the VAR (1) model. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The highest adjusted R^2 statistic is almost 16%, reported for the VASEX index, whereas the lowest adjusted R^2 statistic is 2.57% reported for the VSMI index. For the VIX, VDAX, VCAC and VSTOXX indices the adjusted R^2 statistics are 3.88%, 3.35%, 4.84% and 4.81% respectively. This means that the Greek implied volatility index, VASEX, is more affected by implied volatility movements that are realized in other markets than the other indices. We can say that implied volatility spillovers do exist among the markets. What we can also say is that the lagged values of the VIX and VSTOXX indices are those which most influence the other indices, as their estimated coefficients are statistically different from zero in most cases.

The indices used in the model are all European market volatility indices, except for the VIX index. So, the fact that the VSTOXX index transmits its volatility to them was anticipated. The changes of the VIX index's lagged values are significant for the evolution of the VSTOXX and VDAX index. As far as it concerns the VASEX index, the results imply that its changes are affected by the first lagged values of the changes in the VCAC and VSMI index. The coefficients are 0.2538 and 0.1433 respectively and they are significant at 5% significance level. The first order lagged values of VASEX, affect the evolution of the VCAC index as the estimated coefficient is statistically significant at 10% significance level. However, the impact of its changes is very small as we can see that the coefficient is just -0.0689.

VAR(1) model						
	ΔVASEX	*ΔVIX*	*ΔVDAX*	*ΔVCAC*	*ΔVSTOXX*	*ΔVSMI*
C	0,000	0,000	0,000	0,000	0,000	0,000
	(0,221)	(0,240)	(0,094)	(0,160)	(0,155)	(0,090)
ΔVASEX(-1)	-0,411*	0,028	-0,028	-0,069***	-0,035	0,023
	(-10,939)	(-0,835)	(-0,814)	(-1,902)	(-0,970)	(0,941)
ΔVIX(-1)	-0,004	-0,253*	0,188*	0,272	0,267*	0,006
	(-0,060)	(-4,887)	(3,565)	(4,805)	(4,777)	(0,164)
ΔVDAX(-1)	-0,018	0,195	-0,100	0,108	0,122	0,098
	(-0,131)	(1,604)	(-0,811)	(0,813)	(0,932)	(1,086)
ΔVCAC(-1)	0,254**	0,154***	0,069	-0,128	0,120	0,007
	(2,663)	(1,822)	(0,807)	(-1,388)	(1,322)	(0,116)
ΔVSTOXX(-1)	-0,180	-0,207***	-0,207***	-0,241***	-0,489*	0,015
	(-1,333)	(-1,732)	(-1,704)	(-1,850)	(-3,796)	(0,166)
ΔVSMI(-1)	0,143**	-0,004	-0,028	-0,027	0,025	0,008
	(2,308)	(-0,067)	(-0,495)	(-0,444)	(0,420)	(0,186)
AIC	-5,58	-5,83	-5,79	-5,65	-5,68	-6,43
BIC	-5,53	-5,78	-5,74	-5,60	-5,63	-6,38
Adj. R^2	15,99%	3,88%	3,35%	4,84%	4,81%	2,57%

Table (12): Implied volatility spillovers across markets. The entries report results from the following VAR(1) model: $\Delta IV_t = C + \Phi \Delta IV_{t-1} + \varepsilon_t$, where $\Delta IV_t = IV_t - IV_{t-1}$ is the (6×1) vector of changed in the implied volatility indices between t-1 and t, *C* is a (6×1) matrix of constants, Φ is a (6×6) matrix of coefficients and ε is a (6 x 1) vector of residuals. The number of lags has been chosen so as to minimize the BIC and to keep the model parsimonious. Closing prices for the U.S. and the European implied volatility indices have been used. The estimated coefficients, *t*-statistics in parentheses and the adjusted R^2 are reported. One, two and three asterisks denote rejection of the null hypothesis of a zero coefficient at the 1%, 5% and 10% level, respectively. The model has been estimated for the period January 2004 to July 2008.

After the parameters of the VAR model have been estimated, we test the stability of the model. In order for the VAR model to be stable (or stationary) all the inverse roots of the characteristic AR polynomial must have modulus less than one and lie inside the unit circle. The results from the VAR Stability Condition Check show that no root lies outside the unit circle and hence, confirm that the model is stable.

5.3.2 Granger Causality tests

To investigate furthermore the volatility spillovers across international markets we also run pairwise Granger causality tests for the implied volatility indices. The tests were executed both for a lag length of two and for a lag length of four. The results are presented in tables (13) and (14). In table (13) we can see the Granger causality tests between VASEX and each one of the other indices in study. Table (14) provides us the results of the tests among the other indices.

Granger Causality for Implied Volatility Indices				
Null Hypothesis:	*2 lags*		*4 lags*	
	F-Statistic	**Probability**	**F-Statistic**	**Probability**
ΔVIX does not Granger Cause ΔVASEX	2,35	0,096	4,83**	0,001
ΔVASEX does not Granger Cause ΔVIX	1,30	0,273	0,82	0,512
ΔVDAX does not Granger Cause ΔVASEX	2,96	0,052	5,24**	0,000
ΔVASEX does not Granger Cause ΔVDAX	1,43	0,240	0,94	0,441
ΔVCAC does not Granger Cause ΔVASEX	6,34**	0,002	7,15**	0,000
ΔVASEX does not Granger Cause ΔVCAC	2,20	0,112	1,06	0,376
ΔVSTOXX does not Granger Cause ΔVASEX	2,88	0,057	5,06**	0,001
ΔVASEX does not Granger Cause ΔVSTOXX	0,98	0,375	0,74	0,565
ΔVSMI does not Granger Cause ΔVASEX	5,95**	0,003	3,49**	0,008
ΔVASEX does not Granger Cause ΔVSMI	2,29	0,102	2,75*	0,028

Table (13): Granger Causality tests using 2 and 4 lags. The table reports the F-statistics and the probability for the pairwise bivariate regressions between the changes, Δ, in the level of VASEX index and the changes in the level of each one of the other indices in study. The data spans the period January 2004 to July 2008.

As we see, when using two lags for the Granger causality test ΔVCAC and ΔVSMI do Granger-cause ΔVASEX, as the null hypothesis is rejected at 1% significance level. When we extend the testing, using four lags all the indices in study do Granger-cause ΔVASEX, with the null hypothesis been rejected at 1% significance level. From the other hand ΔVASEX does not Granger-causes none of the indices, but ΔVSMI as the null hypothesis can be rejected at a 5% significance level. In the cases of VIX, VDAX and VSTOXX it is noteworthy is that the null hypothesis that their changes do not Granger-cause the change in the level of VASEX is rejected at 1%

significance level when using four lags, whereas when including two lags the null hypothesis can be rejected only at a 10% significance level. This means that the information content of the changes in these indices is not fully incorporated directly to the movement of VASEX index. These findings are in line with Siriopoulos and Fassas (2008) suggesting that the transmission of the implied volatility across international markets has increased.

The results of the Granger causality tests among the other indices imply that almost all indices do have some explanatory power for the changes of the each other. The indices that do not provide any information content for the evolution of each other are VDAX, VCAC and VSTOXX. The pairwise Granger causality tests for those reveal that there is not any Granger causality relationship among them. The only exception of this, is the case of the causality test between VCAC and VSTOXX using four lags, where we can see that the changes of VCAC (ΔVCAC) do Granger-cause the changes of VSTOXX (ΔVSTOXX), as the F-statistic of the regression is 2.2498 implying significance at a 10% level.

We should mention that the changes of the VIX index do Granger-cause the changes of all the other indices as the null hypothesis is rejected at a significance level of 1%. This implies that the CBOE's index is indeed the one that transmits the implied volatility to each other international market. This finding is in line with the existing literature. See for example, Siriopoulos and Fassas (2008), whose findings do confirm the leading nature of the VIX index in the concept of transmitting volatility across the globe.

Granger Causality for Implied Volatility Indices				
Null Hypothesis:	*2 lags*		*4 lags*	
	F-Statistic	**Probability**	**F-Statistic**	**Probability**
ΔVDAX does not Granger Cause ΔVIX	4,03*	0,018	3,82**	0,004
ΔVIX does not Granger Cause ΔVDAX	10,43**	0,000	4,96**	0,001
ΔVCAC does not Granger Cause ΔVIX	5,42**	0,005	4,39**	0,002
ΔVIX does not Granger Cause ΔVCAC	15,11**	0,000	7,50**	0,000
ΔVSTOXX does not Granger Cause ΔVIX	2,59	0,076	2,70*	0,030
ΔVIX does not Granger Cause ΔVSTOXX	17,63**	0,000	8,65**	0,000
ΔVSMI does not Granger Cause ΔVIX	0,12	0,886	0,26	0,901
ΔVIX does not Granger Cause ΔVSMI	18,35**	0,000	14,29**	0,000
ΔVCAC does not Granger Cause ΔVDAX	2,52	0,081	1,75	0,138
ΔVDAX does not Granger Cause ΔVCAC	0,10	0,902	1,13	0,341
ΔVSTOXX does not Granger Cause ΔVDAX	1,51	0,222	0,89	0,471
ΔVDAX does not Granger Cause ΔVSTOXX	1,04	0,356	1,39	0,237
ΔVSMI does not Granger Cause ΔVDAX	0,62	0,536	0,64	0,635
ΔVDAX does not Granger Cause ΔVSMI	29,35**	0,000	22,07**	0,000
ΔVSTOXX does not Granger Cause ΔVCAC	0,55	0,576	1,72	0,143
ΔVCAC does not Granger Cause ΔVSTOXX	2,17	0,114	2,25	0,062
ΔVSMI does not Granger Cause ΔVCAC	0,40	0,673	0,48	0,747
ΔVCAC does not Granger Cause ΔVSMI	25,56**	0,000	20,33**	0,000
ΔVSMI does not Granger Cause ΔVSTOXX	0,33	0,716	0,13	0,971
ΔVSTOXX does not Granger Cause ΔVSMI	30,24**	0,000	20,88**	0,000

Table (14): Granger Causality tests using 2 and 4 lags. The table reports the F-statistics and the probability for the pairwise bivariate regressions between the changes, Δ, in the levels of the indices in study, except for VASEX. The data spans the period January 2004 to July 2008.

Section 6
The Relationship between Implied and Realized Volatility

The implied volatility is widely regarded as the market's forecast of the future volatility of the underlying asset's returns over a specific time horizon. Moreover, if the markets are efficient then implied volatility should be an efficient prediction of the future realized volatility. This means that the implied volatility should contain all the available information of the market (Christensen and Prabhala, 1998).

In this section we test whether the implied volatility can provide any information about the future realized volatility and if this information is superior to the pure past realized volatility.

We use two measures of the implied volatility, the model-free implied volatility and the Black-Scholes implied volatility. Toward this point, we construct a second implied volatility index, following Skiadopoulos (2004) methodology. Since the latter is a Black-Scholes based measure, it allows us to investigate whether its information content is fully subsumed by the model-free implied volatility. This is an argument of great interest, as recently a lot of research is done in this field [see for example Jiang and Tian (2005)]. However, to the best of our knowledge no previous research exists for the case of the Greek market and is limited for the cases of illiquid and low depth markets.

6.1 Construction of GVIX

In this subsection we construct a second implied volatility index for the Greek market, named GVIX following Skiadopoulos (2004) methodology. Let us first introduce the steps of this construction method.

In order to construct the index, we need for each day four options, two for each maturity. The options needed are the first available OTM options, one call and one put, for each maturity. The prices of the call and put options are first transformed into implied volatilities using an options valuation model.

In our study, we will do a change of the original methodology. Skiadopoulos (2004) used the Black's (1976) model that prices futures options in order to extract the implied volatilities of the options. He did so, to deal with the fact that the underlying asset, FTSE/ASE-20, is a dividend paying asset and data for the dividend yields are not available. The only prerequisite for the model to hold is that the options and futures contracts used have the same time to expiration. This is not applicable in our case because ADEX, since the beginning of 2007 has stopped introducing futures contracts for the two shortest expiries that we have for the options contracts. Hence, the options valuation model that we use is the Black-Scholes (1973) and Merton (1973) model. The dividend yield needed is already calculated before (implied dividend yield), using the Ait-Sahalia and Lo (1998) method.

The mathematical expression of the Black-Scholes-Merton (1973) model is:

$$c = S_0 N(d_1) - K e^{-rT} N(d_2)$$

$$p = K e^{-rT} N(-d_2) - S_0 N(-d_1)$$

Where

$$d_1 = \frac{\ln\left(\frac{S_0}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)}{\sigma\sqrt{T}}, \qquad d_2 = d_1 - \sigma\sqrt{T}$$

N(x) is the probability that a normally distributed variable with a mean of zero and a standard deviation of 1 is less than x.

All the inputs, except for σ are known. Solving the equation for σ, we extract the implied volatility of each option. In order to get the implied volatility we proceed as follows:

Step 1

Interpolate between the nearby implied volatilities and the second-nearby implied volatilities to get an at-the-money implied volatility for each maturity. The ATM nearby and second nearby implied volatilities (σ_1 and σ_2, respectively) are:

$$\sigma_1 = \sigma_1^{X_l}\left(\frac{X_u - S}{X_u - X_l}\right) + \sigma_1^{X_u}\left(\frac{S - X_l}{X_u - X_l}\right)$$

And

$$\sigma_2 = \sigma_2^{X_l}\left(\frac{X_u - S}{X_u - X_l}\right) + \sigma_2^{X_u}\left(\frac{S - X_l}{X_u - X_l}\right)$$

Where

σ_1 is the implied volatility of the at-the-money nearby contracts,

σ_2 is the implied volatility of the at-the-money second-nearby contracts,

$\sigma_1^{X_l}$ is the implied volatility of the first nearby OTM put option,

$\sigma_1^{X_u}$ is the implied volatility of the first nearby OTM call option,

$\sigma_2^{X_l}$ is the implied volatility of the first second-nearby OTM put option,

$\sigma_2^{X_u}$ is the implied volatility of the first second-nearby OTM call option,

X_l is the strike price of the corresponding first OTM put option for each maturity

and

X_u is the strike price of the corresponding first OTM call option for each maturity

Step 2 – Final

The final step is to interpolate linearly between the nearby and second nearby implied volatilities to create a thirty calendar day (or 22 trading day) implied volatility.

$$\sigma = \sigma_1\left(\frac{N_{t_2} - 22}{N_{t_2} - N_{t_1}}\right) + \sigma_2\left(\frac{22 - N_{t_1}}{N_{t_2} - N_{t_1}}\right)$$

It should be noted that in line with Whaley the implied volatility is based on trading days. So, if the time to expiration of an option is calculated using calendar days, we will end up with a volatility rate per calendar day. Working this way, would meant that the variance of the returns on the stock indices over the weekends should be three times higher than it is over any other pair of trading days during a week. This is empirically rejected. As a consequence, we use trading days in the determination of the implied volatility.

The formula used to transform the calendar days to trading days is according to Whaley:

$$N_t = N_c - 2 \times int(N_c/7)$$

Where

N_t is the number of trading days until expiration and

N_c is the number of calendar days until expiration.

The implied volatility rate is multiplied by the ratio of the square root of the number of calendar days to the square root of the number of trading days, that is:

$$\sigma_t = \sigma_c \left(\frac{\sqrt{N_c}}{\sqrt{N_t}} \right)$$

Where σ_t is the trading day implied volatility rate and σ_c is the calendar day implied volatility rate.

6.2 Properties of GVIX and comparison with VASEX's properties

Figure () shows the evolution of the two Greek implied volatility indices through the period January 2004 to December 2008. Table 15 shows the summary statistics (mean, median, maximum, minimum, standard deviation, skewness, kurtosis and the results from the Jarque-Bera test with its *p*-value in brackets) of the constructed implied volatility indices together. It also presents the first order autocorrelation and the results from the Augmented Dickey-Fuller unit root test statistic.

As can be seen, the index calculated with the old, Skiadopoulos methodology is generally moving in higher levels and is much more volatile than the index calculated with the model-free methodology. The mean of the GVIX is 26.84% while the mean of VASEX is 20.37%. There is also a great difference in the range of the two indices. GVIX has a range of 75.79 percentage points while the VASEX has a range of just 40.28 percentage points. The standard deviation of the GVIX is 10.03% almost double than the standard deviation of VASEX (5.15%). The skewness and the kurtosis of the two indices are very close and they imply longer right tails and that the distributions have fat tails. As we see from the Jarque-Bera statistic they are both not-normally distributed. The highest level of GVIX is 87.70% and was reached on November 17, 2008 and the lowest level was 11.91% reached on November 8 2005. We remind that the highest level of VASEX is 53.12% and was reached on October 10, 2008 and the lowest level was 12.83% reached on November 14 2005.

The fact that GVIX is more volatile is not surprising since it is well documented that an implied volatility index, constructed using the Black-Scholes methodology is usually exhibiting this behavior.

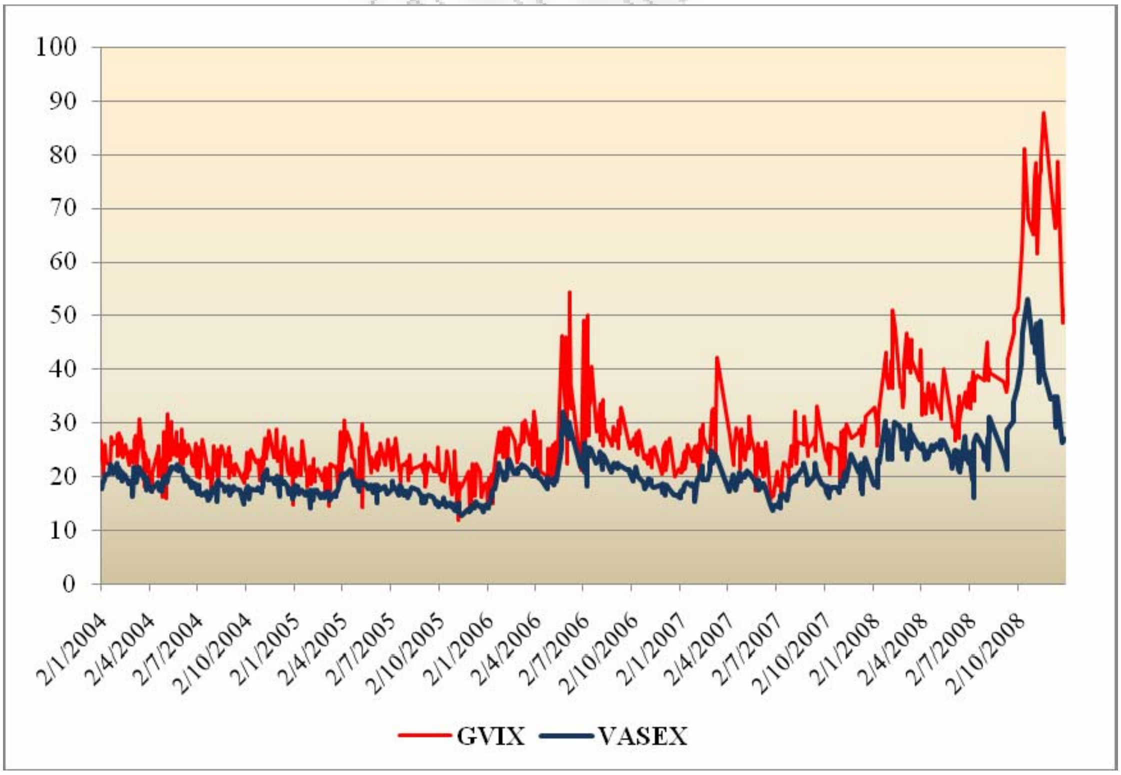

Figure (6): Evolution of the Greek implied volatility indices, VASEX and GVIX. The figure shows the daily evolution of the implied volatility indices over the period January 2004 to December 2008.

Statistics	VASEX	GVIX
Mean	20,37	26,84
Median	19,26	24,34
Minimum	12,83	11,91
Maximum	53,12	87,70
St.Deviation	5,15	10,03
Skewness	2,69	2,89
Kurtosis	13,60	13,66
J-B Stat.	4150,24*	4320,939*
(Probability)	0,001	0,001
ρ_1	0,9291*	0,8813*
ADF	-3,4597*	-4,1189*

Table (15): Summary Statistics of the Greek Implied volatility indices. The entries report the summary statistics for the Greek implied volatility indices GVIX and VASEX. The first order autocorrelation $\rho 1$, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. An asterisk denotes rejection of the null hypothesis at the 1% level. The null hypothesis for the first order autocorrelation, Jarque-Bera and the ADF tests is that the first order autocorrelation is zero, that the series is normally distributed and that the series has a unit root, respectively. The sample spans the period January 2004 to December 2008.

6.3 Methodology implemented for accessing the information content of the volatility forecasts

The methodology used in order to derive the realized volatility is based on the standard practice, followed by the majority of the studies. Christensen and Prabhala have shown, that a sample with non-overlapping data yields more reliable regression estimates relative to regressions using overlapping data. For this reason, we calculate the realized volatilities over a one-month period. Following Corrado and Miller (2005) methodology, for the forecast of the realized volatility, we use the implied volatility value of the last trading day of the previous period. That is, we have the market's expectation for the future realized volatility over the next month, as reflected in the implied volatility of the last trading of the prior month. This procedure ensures that our sample will have not overlapping observations.

However, ADEX options, even the most liquid ones, written on the FTSE/ASE-20 index, are thinly traded, so we cannot have an observation for the implied volatility in the last day of each month. Therefore, we follow a methodology proposed by Hansen (1999), who implemented it on his study about the relationship between implied and realized volatility in the low-liquidity Danish option and equity markets. The steps followed are the following:

- We use the implied volatility of the previous day
- If we have not an observation for the previous day, we move two days forward and use this implied volatility
- If no observation exists at that day either, then we move three days back and use this implied volatility
- If still no observation exists, we move four days forward and use this implied volatility.
- Lastly, if this is not possible, we continue moving one trading day forward and use this implied volatility.

As Hansen (1999) reports, this procedure preserves the non-overlapping nature of the data and makes it possible to avoid the serial correlation errors of the forecast. The greatest deviations from the last trading day were four trading days (e.g. we used the implied volatility of 4/2/2008, rather than the value of 31/1/2008).

There is a debate over the use of trading or calendar days in the realized volatility calculations. Some argue that information arrives even when an exchange is closed and this should influence the price. However, lots of empirical studies have been done and researchers found that volatility is by far greater when the exchange is open than when it is closed. As a consequence, if daily data are used to measure volatility, the results suggest that days when the exchange is closed should be ignored. So, we proceed our study, using trading days. The number of trading days in each month is about twenty-two (except for the months where holidays exist) and the total number of trading days is assumed to be 252.

We construct a time series of realized index returns volatilities. We take into consideration the daily closing prices of the FTSE/ASE-20. The realized volatility is calculated as the standard deviation of the daily index returns over the time period into consideration. That is,

$$\sigma_h = \sqrt{\frac{252}{t}\sum_{k=1}^{T}\left(R_{t,k} - \overline{R}_t\right)^2}$$

Where

σ_η is the realized monthly volatility,

252 is the number of trading days per annum,

t is the number of trading days in every month,

$R_{t,k}$ is the return of the FTSE/ASE-20 index on the day and

$\overline{R_t}$ is the average return over the period into consideration.

6.4 Empirical Results

Consistent with prior research [i.e., Christensen and Prabhala (1998), Hansen (1999) and Jiang and Tian (2005)], we employ both univariate and encompassing regressions to analyze the information content of volatility forecasts. In a univariate regression framework, realized volatility is regressed against a single volatility forecast. The encompassing regressions focus on the relative importance of different volatility forecasts as they use two or more volatility forecasts as explanatory variables for the realized volatility.

The standard practice followed in order to assess the information content of the implied volatility is the estimation of the following regressions:

$$h_t = a_0 + a_1 i_t^{MF} + \varepsilon_t \qquad (6.1)$$

$$h_t = a_0 + a_1 i_t^{BS} + \varepsilon_t \qquad (6.2)$$

Where

h_t stands for the realized volatility for period t, i_t^{MF} stands for the model-free implied volatility at the beginning of the period t (or, as explained before, the end of the period t-1) and i_t^{BS} stands for the Black-Scholes implied volatility.

According to Christensen and Prabhala (1998), via this regression we can examine at least three hypotheses.

- First, if implied volatility carries some information about the future realized volatility α_1 should not be zero.
- Second, if the implied volatility is an unbiased predictor of the future realized volatility, then $a_0 = 0$ and $a_1 = 1$
- Finally, if implied volatility is efficient, the residuals ε_t of the regression should be a white noise process and uncorrelated with any variable in the market's information set.

Another debate on the literature is whether to use the raw series for the volatility measures or their natural logarithms. Christensen and Prabhala (1998) and Hansen (1999) for example transform the raw series into logarithmic form. They do so, since the logarithm of volatility is usually closer to the Normal distribution than volatility itself. In contrast Fleming (1998) uses the raw data series. Jiang and Tian (2005) use both the levels and the logarithms of the volatility measures. In this study, we use both methods.

Also, in order to examine whether the past realized volatility can forecast the evolution of the future realized volatility, we run the following regression:

$$h_t = a_0 + a_1 h_{t-1} + \varepsilon_t \tag{6.3}$$

Table (16) summarizes the results of the univariate regressions (6.1), (6.2) and (6.3).

	Univariate Regressions					
	Dependent Variable: Realized Volatility (h_t)					
	Panel A: *Results from equations* (6,1), (6,2) and (6,3) --- *raw-series data*					
	Independent Variables				**Adjusted R^2**	**D - W**
	intercept	i_t^{MF}	i_t^{BS}	h_{t-1}		
Coeff.	-0,13***	1,64*	–	–	49,94%	1,79
t-stat.	(-2,00)	(4,69)	–	–		
Coeff.	-0,01	–	0,76*	–	43,76%	1,72
t-stat.	(-0,16)	–	(3,55)	–		
Coeff.	0,08*	–	–	0,63*	38,70%	2,08
t-stat.	(2,95)	–	–	(4,11)		
	Panel B*: Results from equations* (6,1), (6,2) and (6,3) - *log-transformed data*					
Coeff.	0,58***	1,42*	–	–	45,12%	1,83
t-stat.	(1,89)	(7,78)	–	–		
Coeff.	-0,37	–	1,01*	–	43,91%	1,92
t-stat.	(-1,49)	–	(5,90)	–		
Coeff.	-0,62*	–	–	0,63*	38,49%	2,24
t-stat.	(3,20)	–	–	(6,41)		

Table (16): Test for the information content of the volatility measures. Reported values are the estimated coefficients of the univariate regressions (6.1), (6.2) and (6.3). Panel A refers to the regressions estimated using the raw data set and Panel B refers to the regression estimated using log-transformed volatility series. Heteroskedasticity consistent White standard errors were estimated and the corrected t-statistics are reported. One, two and three asterisks denote the rejection of the null hypothesis of a zero coefficient at 1%, 5% and 10% significance level respectively.

As can be seen, all the implied volatility measures do contain some information about the future realized volatility as the estimated coefficients are all statistically different from zero at 1% significance level. This is true both for the levels and for the logarithms of the series. The Durbin-Watson statistic is not statistically significant from two in every regression, thus indicating that there is no serial-correlation in the errors. In the regressions conducted using the raw-data series, the model-free implied volatility yields higher adjusted R-squared. However, this is stronger for the cases where we use the raw data series. Interestingly, the log-transformed BS implied volatility appears to be an efficient and unbiased forecast of the future realized volatility. The estimated coefficient of the intercept is -0.37 and is not statistically different from zero and the estimated coefficient of i_t^{BS} is 1.01 which is very close to unity.

Next, we examine whether the information content of the implied volatility is superior to the information content of the past realized volatility, meaning that implied volatility contains all the information of the past realized volatility in explaining the future realized volatility.

We proceed into the estimation of the following regressions:

$$h_t = a_0 + a_1 i_t^{MF} + a_2 h_{t-1} + \varepsilon_t \qquad (6.4)$$

$$h_t = a_0 + a_1 i_t^{BS} + a_2 h_{t-1} + \varepsilon_t \qquad (6.5)$$

Where

h_t stands for realized volatility, as before and h_{t-1} stands for the realized volatility of the previous month. i_t^{MF} and i_t^{BS} stand for the model-free implied volatility and the Black-Scholes implied volatility respectively.

As in the previous tests, we use both the levels and the log-transformed of the volatility measures. The results of the regressions are given below in table (17). The results obtained before [Table (16)] give support to the fact that historical volatility alone can help predict the future realized volatility with the obtained adjusted R-squared to be around 39% for both the regression in the levels and in the log-transformed values of the realized volatility. However, when measures of the implied volatility, either model-free or Black-Scholes, are incorporated in the regressions the estimated coefficients for the past realized volatility are becoming lower and statistically insignificant. Hence, both measures of implied volatility do contain all the information that historical volatility carries.

Interestingly, as noted in the previous regressions when considering the levels of the time series the model-free implied volatility can explain a greater part of the regression. It yields a greater adjusted R-squared (49.53%) than the BS implied volatility (43.38%). However, when log-transformed series are taken into account the obtained adjusted R-squared values are again higher for the MF implied volatility but the difference between them is smaller.

Encompassing Regressions						
	Dependent Variable: Realized Volatility (h_t)					
	Panel A: ***Results from equations*** **(6,4) and (6,5) ---** ***raw-series data***					
	Independent Variables				Adjusted R^2	D - W
	intercept	i_t^{MF}	i_t^{BS}	h_{t-1}		
Coeff.	-0,15***	1,81*	–	-0,08	49,53%	1,73
t-stat.	(-1,94)	(3,51)	–	(-0,48)		
Coeff.	0,00	–	0,59	0,17	43,38%	1,82
t-stat.	(0,11)	–	(1,55)	(0,57)		
	Panel B: ***Results from equation*** **(6,4) and (6,5) ---** ***log-transformed data***					
Coeff.	0,41	1,15*	–	0,16	45,26%	1,97
t-stat.	(1,04)	(3,09)	–	(0,98)		
Coeff.	-0,35	–	0,72**	0,23	44,71%	2,09
t-stat.	(-1,44)	–	(2,43)	(1,33)		

Table (17): Test for the superiority of the information content of the implied volatility measures over that of past realized volatility. Reported values are the estimated coefficients of the encompassing regressions (6.4) and (6.5) Panel A refers to the regression estimated using the raw data set and Panel B refers to the regression estimated using log-transformed volatility series. Heteroskedasticity consistent White standard errors were estimated and the corrected t-statistics are reported. One, two and three asterisks denote the rejection of the null hypothesis of a zero coefficient at 1%, 5% and 10% significance level respectively.

In order to investigate whether the information content of the model-free or the BS implied volatility is superior, we use the following equations:

$$h_t = a_0 + a_1 i_t^{MF} + a_2 i_t^{BS} + \varepsilon_t \tag{6.6}$$

$$h_t = a_0 + a_1 i_t^{MF} + a_2 i_t^{BS} + a_3 h_{t-1} + \varepsilon_t \tag{6.7}$$

The results of the regressions are given below, in table (18).On one hand, the results from the regressions in the levels show that the model-free implied volatility subsumes all the information content of the BS implied volatility. We see that the R^2 obtained is around 49%. In the previous regressions where we regressed the future realized volatility on the MF implied volatility and on the MF implied volatility together with the past realized volatility the R^2 obtained was around 50%. Moreover, the estimated coefficient for the BS implied volatility in both regressions (6.6) and (6.7) is statistically insignificant. Hence suggesting that MF implied volatility by aggregating information across strips of options with different strike prices, retains more information about the future realized volatility than the BS implied volatility does.

On the other hand, the results from the regressions in the log-transformed series are quite different. We observe that none of the estimated coefficients for the volatility forecasts is statistically different from zero, as the t-statistics (computed using heteroskedasticity consistent White standard errors) cannot reject the null hypothesis of a zero coefficient. Nevertheless, we see that the R^2 statistics are slightly higher than the R^2 statistics that the univariate and encompassing regressions between the pairs MF implied volatility - past realized volatility and BS implied volatility – past realized volatility yielded. A clear answer cannot be given. Maybe the fact that the liquidity of the market does not provide as much data as would be preferred (such as the availability of data for the U.S. market) for the model-free implied volatility construction does play some role.

What is clear though is the fact that both measures of implied volatility can provide a better forecast for the future realized volatility than the historical volatility can.

Encompassing Regressions						
	Dependent Variable: Realized Volatility (*h_t*)					
	Panel A: *Results from equations* (6,6) and (6,7) --- *raw-series data*					
	Independent Variables				**Adjusted R^2**	**D - W**
	intercept	i_t^{MF}	i_t^{BS}	h_{t-1}		
Coeff.	-0,12	1,42	0,12	–	49,22%	1,79
t-stat.	(-1,39)	(1,59)	(0,28)	–		
Coeff.	-0,14***	1,63***	0,15	-0,13	48,86%	1,70
t-stat.	(-1,73)	(1,91)	(0,33)	(-0,62)		
	Panel B*: Results from equation* (6,6) and (6,7) --- *log-transformed data*					
Coeff.	0,26	0,83	0,48	–	46,31%	1,93
t-stat.	(0,66)	(1,66)	(1,26)	–		
Coeff.	0,21	0,75	0,42	0,09	45,81%	1,98
t-stat.	(0,49)	(1,41)	(1,04)	(0,51)		

Table (18): Test for the superiority of the information content of implied volatility forecasts. Reported values are the estimated coefficients of the encompassing regressions (6.6) and (6.7). Panel A refers to the regression estimated using the raw data set and Panel B refers to the regression estimated using log-transformed volatility series. Heteroskedasticity consistent White standard errors were estimated and the corrected t-statistics are reported. One, two and three asterisks denote the rejection of the null hypothesis of a zero coefficient at 1%, 5% and 10% significance level respectively.

Section 7
Conclusions

The purpose of this dissertation was to construct an implied volatility index for the Greek market. The construction methodology was the new CBOE's, model-free methodology which we have reinforced with a recently developed tool that is the cubic spline interpolation. This was done in order to have a more accurate measure of the implied volatility and since the liquidity of the Greek market is limited, making the methodology not applicable in much cases, due to technical reasons. Next, the properties of VASEX were examined.

In line with Whaley (2000), Giot (2002a) and within the domestic literature Skiadopoulos (2004) and Siriopoulos and Fassas (2008), we verified the existence of the so-called "leverage effect" that is the negative contemporaneous relationship between the changes of VASEX and the underlying's stock index FTSE/ASE-20 returns and hence can be used as a gauge of the investor's fear.

The tests for the existence of an asymmetric leverage effect though were confusing. More specifically the results implied that whatever the evolution of the changes in the levels of VASEX was, the response of the FTSE/ASE-20 would be negative returns, as the estimated coefficient for ΔVASEX was found positive. This is in contrast to our empirical findings relative to the negative relation between the changes of VASEX and the returns of FTSE/ASE-20. The only possible explanation is the extremely powerful effect of the recent global crisis on the risk-return relationship. The subsequent testing for the above mentioned impact revealed that the global financial crisis is indeed the source of this disturbance.

The implemented Granger causality tests between the changes of VASEX and the returns of FTSE/ASE-20 showed that both indices contain some information useful for the prediction of the other, verifying Siriopoulos and Fassas (2008) findings. However, the information contained in VASEX for the FTSE/ASE-20 is limited. What seems to have stronger validity is the power of the lagged FTSE/ASE-20 returns to help predict the future changes of the implied volatility index. This finding implies that an investor can use the information contained in the values of VASEX and the FTSE/ASE-20 of the past one or two periods in order to develop a profitable option strategy.

Next, in line with Giot (2005) we examined whether VASEX can provide a tool to the investors for profitable trading strategies triggered by extremely high levels of implied volatility. Our findings do not support the hypothesis that VASEX is a leading-market indicator. Nevertheless, they do give support to our argument about the disturbance of the risk-return relationship discussed previously, since they reveal the not favorable changes of the risk-return relationship as we move towards to higher implied volatility levels. Moreover, they suggest that entering a long position on the FTSE/ASE-20 index when implied volatility is peaking (like the period of the 2008 financial crisis) leads to great losses, while for the lowest implied volatility levels the returns are relative high.

We proceeded into the examination of volatility spillovers across international markets. We implemented a VAR model and Granger causality tests. The results showed that almost all the included indices (VIX, VDAX, VSTOXX, VCAC and VSMI) do have some explanatory power for the changes of VASEX. However, the information content of the changes in these indices is not fully incorporated directly to the movement of GVIX index, as the Granger causality tests revealed that all the other five indices studied do Granger-cause VASEX when using four lags (for the cases of VCAC and VSMI we find a causality from the second lag). On the other hand, the results support that VASEX does not Granger-causes any of these indices, but the Swiss VSMI.

Moreover, the VAR model showed that the Greek implied volatility index VASEX is more affected by implied volatility movements of the international markets than the other indices, since inside the VAR system its adjusted R^2 value is significantly higher than any other such value in the system. Also, in line with the current literature we find that VIX index is indeed the one that transmits the implied volatility to each other international market, as the lagged values of its changes do Granger-cause each other index. The results also reveal the VSTOXX index changes' intense effect to the movement of each other index. In general, the findings suggest that the transmission of the implied volatility across international markets has increased.

Finally, we were concerned about the information content of the implied volatility with a view to the forecast of the future realized volatility. Toward this point, we constructed a second implied volatility index, named GVIX following Skiadopoulos (2004) methodology. Since the latter is a Black-Scholes (BS) based measure, it allows us to investigate whether its information content is fully subsumed by the model-free (MF) implied volatility.

Our results support, in line with the relative literature that both measures of implied volatility are superior forecasts of the future realized volatility, compared to historical volatility. Moreover, the log-transformed BS implied volatility appears to be an efficient and unbiased forecast of the future realized volatility. As to whether or not the MF implied volatility subsumes all the information contained in the BS implied volatility the results were not clear for sure.

On one hand, the results from the regressions in the raw-series data show that the MF implied volatility subsumes all the information content of the BS implied volatility as the adjusted R^2 from the regressions do not increase when incorporating the latter in the regressors' set. Actually, the highest adjusted R^2 arises when taking into account as explanatory variable only the MF implied volatility. On the other hand, the results from the regressions in the log-transformed series are quite different, since they do not provide clear evidence neither for, nor against the superiority of the MF's implied volatility information content. Nevertheless, they do give some limited support for the superiority of the MF implied volatility since including this regressor as explanatory variable the regressions' adjusted R^2 are in general higher. Maybe, the results would be clearer if the market depth was wider; allowing the model-free implied volatility to incorporate more information. As Whaley (2009) states for the implementation of the MF implied volatility "The only important requisite is that the underlying index option market has deep and active trading across a broad range of exercise prices".

What is clear though is the fact that both measures of implied volatility can provide a better forecast for the future realized volatility than the historical volatility do. So, they are both useful and can be implemented in the Greek market. This is a very important finding since it has many useful applications. For example, the volatility forecasting is extremely crucial for Value-at-Risk (VaR) purposes. Implied volatility can be applied within this framework, since it provides a better prediction of the future realized volatility and subsequently of the value-at-risk. Implied volatility can also be applied for portfolio management purposes, as a forward looking measure of the risk undertaken by investors. Further research could be done by examining these aspects.

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