Essays on the Efficiency of Volatility Derivatives Markets

by

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List of Abbreviations

ADF	Augmented Dickey Fuller
ATM	At-the-Money
CBOE	Chicago Board Options Exchange
CCI	Consumer Confidence Index
CPI	Consumer Price Index
DGO	Durable Goods Orders
DJIA	Dow Jones Industrial Average
ECB	ECB Interest Rate
EU-CCI	Euro-zone Consumer Confidence Index
EU-CPI	Euro-zone Consumer Price Index
EU-GDP	Euro-zone Gross Domestic Product
EU-PPI	Euro-zone Producer Price Index
EU-RS	Euro-zone Retail Sales
FOMC	FOMC Rate Decision
GDP	Gross Domestic Product
IFO	IFO Business Climate
iid	Independent and Identically Distributed
IJC	Initial Jobless Claims
ISM	ISM Non-Manufacturing
LI	Leading Indicators
MAE	Mean Absolute Prediction Error
MC	Monte Carlo
MCP	Mean Correct Prediction
MDM	Modified Diebold and Mariano (1995) test
MMS	Money Market Services International
NFP	Change in Non-Farm Payrolls
NHS	New Home Sales

List of Abbreviations (Cont'd)

OTM	Out-of-the-Money
PCA	Principal Component Analysis
PCs	Principal Components
PCA Model	Changes of each volatility index are regressed on the previous day values of the first four PCs
PPI	Producer Price Index
RMSE	Root Mean Squared Prediction Error
RS	Retail Sales Less Autos
VAR	Vector Autoregression
ZEW	ZEW Survey

Chapter 1: Introduction

Volatility derivatives are a class of derivative securities whose payoff is determined by some measure of volatility of an underlying asset [see e.g., Carr and Lee (2009) for a review]. They have attracted a considerable amount of attention in past years, since they provide a pure volatility exposure and hence, enable trading and hedging against changes in volatility. Brenner and Galai (1989, 1993) and Whaley (1993) first suggested the introduction of derivatives written on some measure of volatility that would serve as the underlying asset. Since then, a number of volatility derivatives have been traded in the over-the-counter market. On March 26, 2004, the first exchange traded volatility derivatives product was introduced by the Chicago Board Options Exchange (CBOE), namely volatility futures on the implied volatility index VIX.[1] Volatility options and futures on a number of other implied volatility indices have also been introduced ever since.

This thesis investigates the efficiency of volatility derivatives markets by exploring two questions. First, it examines whether the recently inaugurated and fast growing volatility futures markets are efficient. To this end, Jensen's (1978) definition of market efficiency is adopted: a market is efficient with respect to the information set I_t in the case where it is impossible to make economic profits by trading on the basis of this information set. Second, it studies whether implied volatility is transmitted between U.S. and European markets and within the European ones, as well as the role of news announcements within an implied volatility spillover framework. Documentation of implied volatility spillovers and a systematic effect of news announcements has implications for the efficiency of volatility derivatives markets. Given the importance and magnitude of volatility derivatives markets answering these two questions is of particular interest to academics. In addition, from the point of view of a practitioner exploring the efficiency of volatility derivatives markets is important because in the case where the efficient market hypothesis is rejected, market participants can potentially devise profitable trading strategies.

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[1] VIX is an implied volatility index that tracks the implied volatility of a synthetic option on the S&P500 with thirty days to maturity. It was initially introduced in 1993 by the CBOE. In 2003, its definition and construction algorithm changed (see Appendix A for its construction). Since then implied volatility indices on a number of other underlying stock indices and assets, such as exchange rates and commodities, have been introduced. .

An extensive body of research has already investigated whether option markets are efficient. This has been done by means of either the no-arbitrage principle [e.g., put-call parity, boundary conditions, box strategy] or the profitability of trading strategies. The findings of this stream of literature have been mixed. In particular, a number of studies have found that the no-arbitrage relationships are frequently violated in the index option markets indicating that inefficiencies exist [see e.g., Kamara and Miller (1995), Ackert and Tian (2001)]. Regarding the literature that examines whether option markets are efficient á la Jensen (1978), simulated trading strategies based on forecasts of option prices or implied volatility have been considered. In particular, within the Black and Scholes (1973) model, Galai (1977) and Chiras and Manaster (1978) have found evidence of profit opportunities in the equity options market, even after transactions costs are taken into account. Similarly, Goyal and Saretto (2009) have found that there is an economically significant predictable pattern in the dynamics of implied volatility by using information from the cross-section of implied volatilities across various stock options. On the other hand, Gonçalves and Guidolin (2006), Bernales and Guidolin (2010) and Chalamandaris and Tsekrekos (2010) have documented that only a statistically predictable pattern exists for implied volatility across option strike prices and expiry dates (i.e. implied volatility surface); stock index, equity and currency options are considered, respectively. This predictability cannot be exploited in an economically significant way, since no abnormal profits can be obtained when sufficiently high transaction costs are injected. These findings are in line with Harvey and Whaley (1992) who form prediction for the short-term at-the-money implied volatility of index options.

There is also some literature that investigates the efficiency of futures markets in terms of statistical and economic predictability.[2] A number of studies have documented a statistically predictable pattern in futures returns [see e.g, Bessembinder and Chan (1992)]. However, this does not necessarily contradict the market efficiency theory, since this predictability may be attributed to an asset pricing model with time-varying risk-premia. On the other hand, the empirical evidence on the predictability in futures markets under an economic metric is mixed. For instance, Hartzmark (1987) has found that in aggregate,

[2] This stream of literature is distinct from the studies that investigate the efficiency of futures markets in terms of the expectation hypothesis. In the latter case, the research question explored is whether the futures price is an optimal forecast of the underlying spot price to be realized on the contract expiry date [see e.g., Coppola (2008), and Kellard et al. (1999) and the references therein, and Nossman and Wilhelmsson (2009), for a study using VIX futures].

speculators do not earn significant profits in commodity and interest rate futures markets. Yoo and Maddala (1991) have studied commodity and currency futures and found that speculators tend to be profitable. Similar findings were reported by Kho (1996) and Kearns and Manners (2004) who consider various simulated trading rules. Regarding the source of the identified trading profits, Kearns and Manners (2004) attributed them to the inefficiency of the currency futures market. Conversely, Yoo and Maddala (1991) and Kho (1996) found that the reported profits were not abnormal; hence, the efficiency of the considered markets cannot be rejected.

There is also an extensive literature that has investigated whether the volatility of the returns of financial assets is transmitted across markets (see Gagnon and Karolyi, 2006, for an extensive review). Surprisingly, the role of news announcements to explain these volatility linkages empirically has received little attention. To the best of our knowledge, Becker et al. (1995) and Connolly and Wang (1998) are the only studies that have examined whether news about economic fundamentals is a source of volatility spillovers. Their analysis is backward-looking in the sense that their volatility measures rely on historical data (high frequency asset returns and conditional volatility models, respectively). Instead, we examine the impact of news announcements on volatility spillovers by employing *implied volatility* to measure the expected stock market volatility. Implied volatility, by definition, is a forward-looking measure of market volatility (see e.g., Granger and Poon, 2003, for a review of the literature on the information content of implied volatility) and is easily extracted from the option market prices.

In contrast to the voluminous literature devoted to the efficiency of the aforementioned derivatives markets, there is no research on the efficiency of volatility derivatives markets. The literature of volatility derivatives has primarily focused on developing pricing models [see e.g., Zhang et al. (2010), Dotsis et al. (2007), Lin (2007), Zhang and Zhu (2006), Detemple and Osakwe (2000), Grünbichler and Longstaff (1996), Brenner and Galai (1989)], hedging volatility risk [see e.g., Jiang and Oomen (2001)] and studying the dynamics of implied volatility [see e.g., Harvey and Whaley (1992), Dumas et al. (1998), Gonçalves and Guidolin (2006), Dotsis et al. (2007), Bernales and Guidolin (2010)]. Therefore, this thesis makes at least two contributions to the existing literature. First, it studies for the first time the efficiency of volatility derivatives markets. Second, it examines the role of scheduled news announcements within an implied volatility spillover framework. To the best of our knowledge, this approach is novel.

This thesis is structured in three papers. The first two papers answer the first question, namely whether the recently inaugurated and fast growing volatility futures markets are efficient. More specifically, in the *first paper* (Chapter 2) the predictability of major U.S. and European implied volatility indices that serve as the underlying asset to implied volatility futures is examined. Asset pricing models that induce predictable patterns in implied volatility have been developed [see e.g., David and Veronesi (2002)]. In this paper, the predictability of implied volatility is explored by means of both point and interval forecasts that are constructed by alternative model specifications. Various statistical tests are considered and the economic significance of the obtained forecasts is also assessed by way of trading strategies in the CBOE volatility futures markets. With respect to the findings, implied volatility indices are statistically but not economically predictable; trading strategies with volatility futures based on the statistical models that describe the evolution of volatility indices do not yield significant risk-adjusted profits. Hence, the hypothesis that volatility futures markets are efficient cannot be rejected.

The *second paper*, (Chapter 3) investigates the efficiency of volatility futures markets per se rather than resorting to the predictability of the underlying implied volatility index. This is because predictability of the underlying index does not necessarily imply predictability of the price of the respective derivative for at least three reasons. First, there may be other factors/information flows that affect volatility futures markets as well [analogous to the "unspanned stochastic volatility problem" in the interest rate derivatives literature, see e.g., Jarrow et al. (2007), and the references therein]. Second, in the case of VIX futures there is no cost-of-carry relationship, since the underlying index is not a tradable asset. This means that the relationship between changes in the prices of VIX futures and its underlying is not known a priori from a theoretical point of view. Third, volatility futures prices may not always be moving to the same direction with the underlying implied volatility index due to market microstructure effects [see a similar discussion and findings in Bakshi et al. (2000a), who conducted an analysis for call options using intra-day data]. Regarding the empirical findings of this paper, a weakly statistically predictable pattern of the volatility futures prices is documented. However, we found that this predictability cannot be exploited for trading purposes. Hence, the hypothesis that the VIX futures market is efficient cannot be rejected which is consistent with the findings in the first paper of this thesis (i.e. Chapter 2)

The *third paper* (Chapter 4) investigates the role of scheduled news announcements within an implied volatility spillover framework.[3] In particular, this paper examines whether (1) shocks in implied volatility are transmitted both between U.S. and European markets and within European ones, (2) news announcements persist even after the effect of news announcements has been taken into account, and (3) news announcements affect the magnitude of implied volatility spillovers, i.e. whether implied volatility spillovers are significantly different on announcement days as opposed to non-announcement days.

The transmission of implied volatility across international markets has already been investigated [see e.g., Nikkinen et al. (2006), Skiadopoulos (2004), Aboura (2003), Gemmill and Kamiyama (2000)], but without taking into account the potential effect of news announcements. On the other hand, the impact of news releases on implied volatility has also been studied but only within a single country and not a spillover framework [see e.g., Ederington and Lee (1996), Beber and Brandt (2006), and Chen and Clements (2007)]. In contrast to the previous literature, this paper investigates the impact of news announcements in an implied volatility spillover setting. To this end, an extensive dataset of major European and U.S. implied volatility indices and scheduled news announcements items is employed. Both the timing (dummy variables, announcement effect) and the content (surprise variables, surprise effect) of the aggregate, regional and individual releases is examined. Based on vector autoregressive (VAR) modeling framework, implied volatility spillovers are found to exist between and within regions. Furthermore, evidence of volatility contagion is found, since implied volatility spillovers persist after news about economic fundamentals are taken into account. The effect of releases on implied volatility dynamics depends on the degree of aggregation of news and the way that these are modeled. The magnitude of implied volatility spillovers is affected by aggregate and regional releases when their content is taken into account. These findings are consistent with the market efficiency hypothesis for option markets.

[3] In the case of scheduled news announcements, the timing but not the content of the release is known a priori by market participants.

Chapter 2: Can the evolution of implied volatility be forecasted? Evidence from European and U.S. implied volatility indices

Abstract

In this Chapter the question whether the evolution of implied volatility can be forecasted by studying a number of European and U.S. implied volatility indices is addressed. Both point and interval forecasts are formed by alternative model specifications. The statistical and economic significance of these forecasts is examined. The latter is assessed by trading strategies in the recently inaugurated CBOE volatility futures markets. Predictable patterns are detected from a statistical point of view. However, these are not economically significant since no abnormal profits can be attained. Hence, the hypothesis that the volatility futures markets are efficient cannot be rejected.

1. Introduction

The question whether the dynamics of implied volatility per se can be forecasted is of paramount importance to both academics and practitioners.[4] Given that the implied volatility is a reparameterisation of the market option price, this question falls within the vast literature on the predictability of asset prices. In addition, implied volatility is often used as a measure of the market risk and hence it can be used in many asset pricing models. Therefore, understanding whether the variation in implied volatility is predictable can help us understand how expected returns change over time [see e.g., Corrado and Miller (2006)]. From a practitioner's point of view, in the case where market participants can predict changes in implied volatility, then they can possibly form profitable option trading strategies. This will also have implications about the efficiency of the option markets.

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[4] This question is distinct from the question whether implied volatility can forecast the future realised volatility [see e.g., Taylor et al. (2010) and references therein]. There is also some distinct literature that has investigated the dynamics of implied volatilities across options with different strike prices and maturities by means of Principal Components Analysis solely for the purposes of option pricing and hedging [see e.g., Skiadopoulos et al. (1999) and references therein].

Among others, David and Veronesi (2002) and Guidolin and Timmerman (2003) have developed asset pricing models that explain theoretically why implied volatility may change in a predictable fashion. The main idea is that investors' uncertainty about the economic fundamentals (e.g., dividends) affects implied volatility. This uncertainty evolves over time. In the case where it is persistent, the models induce predictable patterns in implied volatility.

The empirical evidence on the predictability of implied volatility is mixed. Gonçalves and Guidolin (2006), Bernales and Guidolin (2010) and Chalamandaris and Tsekrekos (2010) have investigated whether the dynamics of implied volatilities across option strike prices and expiry dates (i.e. implied volatility surface) can be forecasted over different time periods; S&P 500 index options, equity options traded on the CBOE and over the counter currency options have been considered, respectively.[5] These studies find that a statistically predictable pattern. This pattern cannot be exploited in an economically significant way since no abnormal profits can be obtained in the case where sufficiently high transaction costs are injected. Similar findings have been documented by Bedendo and Hodges (2009) who studied the S&P 500 implied volatility across option strike prices (i.e. implied volatility skew), rather than the entire implied volatility surface. There is also some literature that has studied the predictability of short-term at-the-money implied volatility by employing sets of economic variables as predictors. Harvey and Whaley (1992), Guo (2000) and Brooks and Oozeer (2002) have addressed this question in the S&P 100, Philadelphia Stock Exchange currency, and LIFFE long gilt futures options markets, respectively. They found that changes in implied volatility are partially statistically predictable but not economically significant. In a related study, Gemmill and Kamiyama (2000) have found that the changes in the implied volatilities of index options in a specific market are driven by the previous period changes of implied volatilities in another market (lagged spillover effects); the FTSE 100 (UK), NK225 (Japan), and S&P 500 (U.S.) options are employed. However, the economic significance of their results is not examined. On the other hand, Goyal and Saretto (2009) have found that there is both a statistically and economically significant predictable pattern in the dynamics of implied

[5] Note that Dumas et al. (1998) have examined alternative deterministic volatility functions for the purposes of option pricing and hedging. The specifications under scrutiny have been found to be unstable over time. This time variation has been modeled by Gonçalves and Guidolin (2006) who found a statistically predictable pattern.

volatility by using information from the cross-section of implied volatilities across various stock options.

This paper makes at least four contributions to the ongoing discussion about the predictability of implied volatility in equity markets. First, it employs an extensive data set of European and U.S. implied volatility indices. Implied volatility indices have mushroomed over the last 15 years in the European and U.S. markets and have particularly attractive characteristics for the purposes of our analysis as will be discussed below. In addition, the nature of the data set will shed light on whether the results may differ across countries and industry sectors. Second, both point and interval forecasts are formed and evaluated; the previously mentioned papers have only considered point forecasts. Interval forecasts are particularly useful for trading purposes [see e.g., Poon and Pope (2000) for an application to option markets]. Third, we perform a horse race among alternative model specifications so as to check the robustness of the obtained results; tests for predictability form a joint hypothesis test of the question under scrutiny and the assumed model. Finally, the economic significance of the statistical evidence is assessed by means of trading strategies in the newly introduced and fast growing CBOE volatility futures markets. The results will have implications about the efficiency of these markets that has not been investigated yet, as far as we are concerned.

To fix ideas, an implied volatility index tracks the implied volatility of a synthetic option that has constant time-to-maturity. The data on the implied volatility indices are the natural choice to study whether implied volatility is predictable. This is because the various methods to construct the index eliminate measurement errors in the calculated implied volatilities [see Hentschel (2003)], and take into account the traded option prices (or implied volatilities). Moreover, the possible presence of a predictable pattern in the evolution of implied volatility indices is of particular importance because these can be used in a number of applications. They serve as the underlying asset to implied volatility derivatives and they can be interpreted as variance and volatility swap rates.[6] Furthermore, the implied volatility index can also be used for Value-at-Risk purposes [Giot (2005)], to identify profitable opportunities in the stock market [see e.g., Banerjee et

[6] A variance swap is actually a forward contract where the buyer (seller) receives the difference between the realised variance of the returns of a stated index and a fixed variance rate, termed variance swap rate, if the difference is positive (negative). The volatility swap is defined similarly; a volatility rather than a variance index serves as the underlying asset.

al. (2007)], and to forecast the future market volatility [see e.g., Moraux et al. (1999), Giot (2005), Becker et al. (2007) among others].

There are a number of papers that have studied the dynamics of implied volatility indices for the purposes of pricing implied volatility derivatives [see e.g., Dotsis et al. (2007), and the references therein]. However, the question whether the dynamics of implied volatility indices can be predicted has received little attention. To the best of our knowledge, Aboura (2003), Ahoniemi (2008), and Fernandes et al. (2007) are the only related studies. All three studies differ in the time period they consider, focus on a limited number of indices and forecasting models, and provide only point forecasts. They all find that the evolution of implied volatility indices is statistically predictable. Only the second paper examines the economic significance of the obtained forecasts and finds that a trading strategy with the S&P 500 options cannot attain abnormal profits. Our research approach is more general; a range of European and U.S. implied volatility indices is employed over a common time period, point and interval forecasts are formed by a number of alternative model specifications, and both their statistical and economic significance is assessed.

The remainder of the paper is structured as follows. In the next Section, the data sets are described. Section 3 presents the models to be used for forecasting. The in-sample performance of each model is examined in Section 4. The out-of-sample predictive performance of the models and the economic significance of the generated forecasts are evaluated in Sections 5 and 6, respectively and their robustness is examined in Section 7. The last Section concludes.

2. The data set

Daily data on seven implied volatility indices, a set of economic variables (closing prices), and the CBOE volatility futures (settlement prices) are used. The various implied volatility indices have been listed on different dates. Hence, we consider the period from February 2, 2001 to September 28, 2007, so as to study the seven indices over a common time period. The subset from February 2, 2001 to March 17, 2005 will be used for the in-sample evaluation and the remaining data will be used for the out-of-sample one. This choice is dictated by the sample period (March 18, 2005 up to September 28, 2007) spanned by the volatility futures data; these will be used to assess the economic significance of the out-of-sample results.

In particular, four major American (VIX, VXO, VXN, VXD) and three European (VDAX-New, VCAC, and VSTOXX) implied volatility indices are examined. All indices but VXO are constructed by the VIX algorithm [see Appendix A, B and C for the construction and interpretation of implied volatility indices]. VXO is constructed from the implied volatilities of options on the S&P 100. VIX, VXN, and VXD are based on the market prices of options on the S&P 500, Nasdaq 100, and Dow Jones Industrial Average (DJIA) index, respectively. VDAX-New, VCAC and VSTOXX are constructed from the market prices of options on DAX (Germany), CAC 40 (France) and the DJ EURO STOXX 50 index, respectively. The data for VDAX-New and VCAC are obtained from Bloomberg while for the other indices are obtained from the websites of the corresponding exchanges. VXO represents the implied volatility of an at-the-money synthetic option with constant time-to-maturity (thirty calendar days) at any point in time. We study the adjusted VXO, $VXOA = \sqrt{\frac{22}{30}} \times VXO$ rather than VXO itself. This adjustment allows interpreting VXOA as the volatility swap rate under general assumptions; the remaining indices represent the 30-day variance swap rate once they are squared [see Carr and Wu (2006) and the references therein].

The set of economic variables consists of the returns of the stock indices that serve as an underling asset to the options that are used to construct the corresponding volatility indices, the USD Libor and Euribor one-month interbank interest rates, the Euro/USD exchange rate, the WTI and Brent crude oil prices, the slope of the yield curve calculated as the difference between the prices of the 10-year government bond and the one-month interbank interest rate, and the volume of the futures contract of the underlying stock index. The time series of the economic variables were downloaded from Datastream.[7]

The CBOE VIX and VXD volatility futures were listed in March 2004 and April 2005, respectively. The liquidity of these markets keeps increasing. Measured on January 3, 2007, the open interest for the VIX (VXD) futures had increased by 95% (133%). The contract size of the volatility futures is $1000.[8] On any day, up to six near-term serial

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[7] Data on the volume of the S&P 100 futures contract are not available since this contract is not traded.

[8] Prior to March 26, 2007, the underlying asset of the VIX (VXD) futures contract was an "Increased-Value index" termed VBI (DVB) that was 10 times the value of VIX (VXD) at any point in time. The contract size

months and five months on the February quarterly cycle contracts are traded. The contracts are cash settled on the Wednesday that is thirty days prior to the third Friday of the calendar month immediately following the month in which the contract expires. Three time series of futures prices were constructed by ranking the data according to their expiry date: the shortest, second shortest and third shortest maturity series. To minimize the impact of noisy data, we roll to the second shortest series in the case where the shortest contract has less than five days to maturity. Prices that correspond to a volume of less than five contracts were discarded.

Table 2.1 shows the summary statistics of the implied volatility indices (in levels and first differences, Panels A and B, respectively), and volatility futures in levels and first differences (for VIX and VXD, Panels C and D, respectively). Information on the volume in the volatility futures markets is also provided. The augmented Dickey-Fuller (ADF) test for unit roots is also reported. We can see that none of the indices exhibit strong autocorrelation in the daily changes. The values of the ADF test also show that implied volatility indices are non-stationary in the levels, stationary in the first differences though; the same result holds for most of the economic variables (not reported here due to space limitations). The VIX futures are more liquid than the VXD ones, as expected.

3. The forecasting models

3.1 The economic variables model

The economic variables model employs certain economic variables as predictors to forecast the evolution of each implied volatility index [see also Ahoniemi (2008), for a similar approach]. In particular, the following general forecasting specification is employed:

$$\begin{aligned}\Delta IV_t = c_1 + a_1^+ R_{t-1}^+ + a_1^- R_{t-1}^- + \beta_1 i_{t-1} + \gamma_1 fx_{t-1} + \delta_1 oil_{t-1} \\ + \zeta_1 \Delta HV_{t-1} + \rho_1 \Delta IV_{t-1} + \kappa_1 \Delta ys_{t-1} + \xi_1 vol_{t-1} + \varepsilon_t\end{aligned} \quad (2.1)$$

where ΔIV_t denotes the daily changes of the given implied volatility index, c_1 is a constant, and R^+_t, R^-_t denote the corresponding underlying stock index positive and negative log-returns (e.g., R^+_t is filled with the positive returns and zeroes elsewhere), respectively so as to capture the possible presence of the asymmetric effect of index

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of the volatility futures was \$100 times the value of the underlying index. We have rescaled our series accordingly.

returns on implied volatility, i_t denotes the one-month U.S. interbank (Euribor) interest rate for the European (U.S.) market, fx_t the Euro/USD exchange rate, oil_t the WTI (Brent Crude Oil) price for the American (European) market; all three variables are measured in log-differences, ΔHV_t denotes the changes of the 30-days historical volatility, Δys_t the changes of the slope of the yield curve calculated as the difference between the yield of the ten year government bond and the one-month interbank interest rate, and vol_t the volume in log-differences of the futures contract of the underlying index. The choice of these variables is supported by the large literature on the predictability of asset returns [see e.g., Welch and Goyal (2008)]. This is because the implied volatility index is related to the expected return of the underlying stock index and therefore it may be forecasted by these variables [see Harvey and Whaley (1992), for an explanation]. The historical volatility is calculated as a 30-days moving average of equally weighted past squared returns. Furthermore, following Harvey and Whaley (1992) and Guo (2000), we augment the above mentioned set of economic variables by adding the changes of historical volatility and the term ΔIV_{t-1} as explanatory variables.

3.2 Univariate autoregressive and VAR models

Univariate autoregressive and VAR models are employed in order to examine whether the evolution of any given implied volatility index can be forecasted using its previous values, as well as the information from the evolution of implied volatility indices in the other option markets [see also Aboura (2003), for a similar approach]. First, for each implied volatility index an AR(1) model is employed, i.e.:

$$\Delta IV_t = c_1 + \lambda_1 \Delta IV_{t-1} + \varepsilon_t \qquad (2.2)$$

One lag is used since this is found to minimise the BIC criterion (within a range up to ten lags). The VAR specification is given by

$$Y_t = C + \Phi_1 Y_{t-1} + \varepsilon_t \qquad (2.3)$$

where Y_t is the vector of the seven implied volatility indices in their first differences that are assumed to be endogenously (jointly) determined, C is a (7×1) vector of constants, Φ_1, is the (7×7) matrix of coefficients to be estimated, and ε_t is the (7×1) vector of the VAR residuals.

3.3 The principal components model

Principal Components Analysis (PCA) is a non-parametric technique that summarises the dynamics of a set of variables by means of a smaller number of variables (principal components-PCs). Stock and Watson (2002) have shown that PCA can be employed for forecasting purposes. In particular, the PCs are used as predictors in a linear regression equation since they are proven to be consistent estimators of the true latent factors under quite general conditions. Moreover, the forecast constructed from the PCs is shown to converge to the forecast that would be obtained in the case where the latent factors were known. These properties make PCA a very powerful technique for forecasting purposes since it lets the data decide on the predictors to be used. This is in contrast to the approach taken in equations (2.1), (2.2) and (2.3) where the set of forecasting variables was chosen a priori.

First, we apply PCA to the daily changes of implied volatility indices. The first four PCs are retained. Table 2.4 (Panel A) shows the amount of variance explained by each one of the retained first four PCs, as well as the total amount of variance explained by increasing the number of the retained PCs up to four. We can see that first four PCs explain 94% of the total variance of the changes of implied volatility indices. To identify any possible economic interpretation of the retained principal components, the pairwise correlations of the PCs with the economic variables employed in equation (2.1) are calculated [see also Mixon (2002) for a similar approach]. Table 2.4 (Panel B) shows these correlations. We can see that strong correlations appear only in the case of the first two PCs with the returns of the underlying stock indices. This implies that the first two principal components of the changes in IV indices have a common component with the daily returns of all underlying stock markets. Furthermore, to get a better feeling of the results the correlation loadings of the first four PCs are plotted in Figure 2.1. Interestingly, we can see that the first PC moves all implied volatility indices to the same direction, and hence it can be interpreted as a global factor.

Next, the changes of each volatility index are regressed on the previous day values of the first four PCs (PCA model),

$$\Delta IV_t = c_1 + r_1 PC1_{t-1} + r_2 PC2_{t-1} + r_3 PC3_{t-1} + r_4 PC4_{t-1} + \varepsilon_t \tag{2.4}$$

where $r_i, i = 1,...,4$ are coefficients to be estimated.

3.4 ARIMA and ARFIMA models

ARIMA(p,d,q) and ARFIMA(p,d,q) models are employed to take into account the possible presence of short and long memory characteristics in the dynamics of implied volatility, respectively [see Fernandes et al. (2007), for a similar approach]. The ARIMA(p,d,q) specification is given by

$$\Phi(L)\Delta^d IV_t = c + \Theta(L)\varepsilon_t \tag{2.5}$$

where d is an integer that dictates the order of integration needed to produce a stationary and invertible process (in our case d=1), L is the lag operator, $\Phi(L) = 1 + \phi_1 L + ... + \phi_p L^p$ is the autoregressive polynomial, $\Theta(L) = 1 + \theta_1 L + ... + \theta_p L^p$ is the moving average polynomial, μ is the mean of $\Delta^d IV_t$, $c = -\mu(1 + \phi_1 + ... + \phi_p)$, and ε_t is a Gaussian white noise process with zero mean and variance σ_ε^2. The ARFIMA(p,d,q) model is defined by

$$\Phi(L)(1-L)^d (\Delta IV_t - \mu) = \Theta(L)\varepsilon_t \tag{2.6}$$

where now d denotes the non-integer order of fractional integration, $(1-L)^d$ is the fractional difference operator, and μ denotes the expected value of ΔIV_t. In the case where $|d| < 0.5$, the ARFIMA(p,d,q) process is invertible and second-order stationary. In particular, if $0 < d < 0.5$ ($-0.5 < d < 0$) the process is said to exhibit long-memory (antipersistent) in the sense that the sum of the autocorrelation functions diverges to infinity (a constant) [see Baillie (1996), for a review on fractional integration].

We choose p=q=1 based on the BIC criterion and to avoid over-fitting the data (the differences in the BIC values are miniscule across a range of values for p and q). We follow Pong et al. (2004) to estimate the ARFIMA(*1*,*d*,*1*) model and subsequently form the forecasts. In particular, maximum likelihood estimation is performed in the frequency domain by using the Whittle approximation of the Gaussian log-likelihood. Next, forecasts are obtained by taking the infinite autoregressive expansion of the ARFIMA (1,d,1) process. Thus, one-step ahead forecasts are formed by

$$E(IV_{t+1}|I_t) = IV_t + \mu - \sum_{j=1}^{\infty} \pi_j (\Delta IV_{t-j+1} - \mu) \tag{2.7}$$

where $\pi_j = \sum_{i=0}^{j}\left(b_i + \varphi b_{i-1}\right)\left(-\theta\right)^{j-i}$, $b_i = \frac{\Gamma\left(-d+i\right)}{\Gamma\left(-d\right)\Gamma\left(i+1\right)}$ and $\Gamma(\cdot)$ denotes the gamma function. To implement equation (2.7), the infinite summation is truncated at k = 150.

4. In-sample evidence

Tables 2.2, 2.3, 2.5, and 2.6 show the in–sample performance of the economic variables, AR(1)/VAR, PCA, and ARIMA(1,1,1)/ARFIMA(1,d,1) models, respectively. The estimated coefficients, the *t*-statistics within parentheses and the adjusted R^2 are reported for each one of the implied volatility indices, respectively. One and two asterisks indicate that the estimated parameters are statistically significant at 1% and 5% level, respectively. In the case of the economic variables model [Table 2.2] we can see that the adjusted R^2 is nearly zero for all indices and takes the largest value (2.5%) for VCAC. The statistically significant variables for VCAC are CAC's positive return, the lagged changes in historical volatility and the lagged VCAC changes. In the remaining indices, almost all economic variables are insignificant. This comes at no surprise [see e.g., Harvey and Whaley (1992) for similar results on predicting the evolution of the implied volatility of the S&P 100 options]. Interestingly, our results do not depend on the degree of capitalisation of the underlying stock index. This is in contrast to the evidence provided by the literature on the predictability of stock returns where the small size stocks manifest greater predictability compared with big size stocks [see e.g., Fama and French (1988)]. Finally, it should be noticed that the reported results are not subject to problems in statistical inference that arise due to the fact that the predictors may be nearly integrated [see e.g., Ferson et al. (2003)]. This is because the first order autocorrelation coefficient of the changes of each one of the economic variables is well far from unity (the maximum is 0.3 for the interest rate variable).

Table 2.3 (Panel A) shows the results from the AR(1) model [equation (2.2)]. We can see that the adjusted R^2 are zero for all implied volatility indices. The fact that there is no mean-reversion in dynamics of the changes of the implied volatility indices is in contrast to the results found in Dotsis et al. (2007); their results were obtained for a different time period though. Table 2.3 (Panel B) shows the results from the estimation of the VAR model by ordinary least squares (OLS). For each one of the seven equations in the VAR, the estimated coefficients are reported. The greatest value of the adjusted R^2 is obtained for VCAC (11.7%), while the lowest is obtained for VIX (1.2%).

Table 2.5 shows the results from the PCA model [equation (2.4)]. We can see that the model fits poorly most volatility indices; the only exception occurs for VCAC and VSTOXX (R^2=11.2%, R^2=6.8%, respectively). Table 2.6 shows the results for the ARIMA(1,1,1) and the ARFIMA(1,*d*,1) models (Panel A and B, respectively). We can see that the adjusted R^2's are zero for all implied volatility indices. Moreover, the fractional integration parameter is statistically significant in most cases and lies within the range $-0.5 < d < 0$. Therefore, the changes in the implied volatility index do not exhibit long memory. Overall, within sample, the VAR and PCA models perform best. In general, they fit better the European than the U.S. indices. This implies that each European index manifests a certain predictable pattern in its dynamics that could be exploited by the information extracted from the other volatility indices. For instance, VCAC is affected by VXD and VSTOXX, and it affects the other three U.S. indices and VSTOXX.

5. Out-of-sample forecasting performance

We assess the out-of-sample performance of each model specification that we considered in Section 4. The out-of-sample exercise is performed from March 18, 2005 to September 28, 2007 by increasing the sample size by one observation and re-estimating each model as time goes by. Point and interval forecasts are formed for each one of the seven implied volatility indices. Every day, 10,000 simulation runs have been generated to construct the interval forecasts.

5.1 Point forecasts

In line with Gonçalves and Guidolin (2006), we use three metrics to assess the out-of-sample performance of the employed models in a statistical setting: the root mean squared prediction error (RMSE), the mean absolute prediction error (MAE) and the mean correct prediction (MCP) of the direction of change in the value of the implied volatility index [see Gonçalves and Guidolin, 2006, for the definition of each metric]. The models are compared to the random walk model that is used as a benchmark. The modified Diebold Mariano test of Harvey et al. (1997) and a ratio test are used to assess whether any model under consideration outperforms the random walk model in a statistically significant sense under the RMSE/MAE and the MCP metrics, respectively [see Appendix D for a description of the ratio test]. The null hypothesis is that the random walk model and the model under consideration perform equally well.[9]

Table 2.7 shows the results on the out-of-sample performance of the alternative model specifications for each one of the seven implied volatility indices. One and two asterisks denote rejection of the null hypothesis at 1% and 5% significance levels, respectively. There are 35 combinations of implied volatility indices and predictability measures (out of possible total of 126) in which one of the six models has outperformed the random walk. Therefore, in 28% of the cases one of the models performs better than the random walk. This indicates that a statistically predictable pattern exists in the dynamics of implied volatility indices (by assuming independence at a level of significance 5%).

Consistently with the in-sample evidence, the predictable pattern is stronger in the case of the European indices where in 41% (22/54) of the cases, the models under consideration outperform the random walk; in the case of the U.S. indices, only in 18% (13/72) of the cases one of the models outperforms the random walk. Regarding the question which model performs best, the VAR and PCA models outperform all competing models in the case of the European indices since they beat the random walk under all metrics. The ARIMA(1,1,1) and ARFIMA(1,d,1) models perform best in the case of the U.S. indices. The results imply that there are implied volatility spillovers between the markets; the information contained in all implied volatility indices can be used to predict each European index separately. This is not the case for the U.S. indices where instead their autocorrelation structure should be taken into account in order to predict their evolution.

5.2 Interval forecasts

To evaluate the goodness of the out-of-sample interval forecasts, Christoffersen's (1998) likelihood ratio test of unconditional coverage (LR_{unc}) is used. Let an observed sample path $\{IV_t\}_{t=1}^{T}$ of the time series of the implied volatility index and a series of constructed

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9 Strictly speaking, the MCP cannot be calculated under the random walk model. Hence, in the ratio test, we treat the random walk model as a naïve model that would yield MCP=50%.

interval forecasts $\{(L_{t/t-1}(\alpha),\ U_{t/t-1}(\alpha))\}_{t=1}^{T}$ at a significance level *α%*. $L_{t/t-1}(\alpha)$ and $U_{t/t-1}(\alpha)$ denote the constructed at time (*t*-1) lower and upper bound of the *α%*-interval forecast for time *t*, respectively. The null hypothesis is that the (1-*a*)%-interval forecast is "efficient", i.e. that the percentage of times that the realized index value at time *t* falls outside the constructed at time (*t*-1) intervals is *a* %. Given that the power of the test may be sensitive to the sample size, we base the accept/reject decisions of the null hypothesis on Monte Carlo (MC) simulated *p*-values [see Appendix E for a description of the MC procedure].

Table 2.8 shows the percentage of observations that fall outside the constructed 5% intervals, and the values of Christoffersen's (1998) test obtained by the economic variables, AR(1), VAR, PCA, ARIMA(1,1,1), and ARFIMA(1,*d*,1) models (Panels A, B, C, D, E, and F, respectively) for each one of the seven implied volatility indices. One and two asterisks denote rejection of the null hypothesis at 1% and 5% significance levels, respectively. We can see that there is no single model that yields accurate forecasts for all indices just as was the case with the point forecasts; the VAR model performs best in the horse race among models. Overall, the null hypothesis is accepted in 48% of the cases (20 cases out of a possible total of 42). Interestingly, 17 out of these 20 cases pertain to the U.S. indices. These results imply that there is also a predictable pattern in an interval forecast sense that is stronger for the U.S. indices. This is in contrast to the point forecasts case where predictability was stronger for the European indices. On the other hand, the presence of volatility spillovers is useful for forecasting purposes just as was the case in the point forecasts.

6. Economic significance

To assess the economic significance of the point and interval forecasts formed by each one of the six employed models, trading strategies with VIX (VXD) futures are constructed. The strategies employ each one of the three shortest VIX (VXD) futures series. The strategies are implemented for each model separately, despite the fact that some of the models do not generate statistically significant forecasts. This is because the statistical evidence does not always corroborate a financial criterion [see also Ferson et al. (2003)]. The CBOE transaction costs are taken into account ($0.5 per contract).

6.1 Trading strategy based on point forecasts

To assess the economic significance of the point forecasts, the following trading rule is employed. The investor goes long (short) in the volatility futures in the case where the forecasted value of the implied volatility index is greater (smaller) than its current value. Table 2.9 shows the annualised Sharpe ratio (*SR*) and Leland's (1999) alpha (A_p) obtained for each one of the three shortest VIX and VXD futures.[10] Results are reported for the trading strategy based on the point forecasts formed by the economic variables (Panel A), AR(1) (Panel B), VAR (Panel C), PCA (Panel D), ARIMA(1,1,1) (Panel E), and ARFIMA(1,*d*,1) (Panel F) models. To evaluate the statistical significance of *SR* and A_p, 95% confidence intervals have been bootstrapped and reported within parentheses. One asterisk denotes rejection of the null hypothesis of a zero *SR* (A_p) at a 5% level of significance. We can see that *SR* and A_p are statistically insignificant in almost all cases. Therefore, the statistically predictable pattern found in Section 5.1 is not economically significant in that no abnormal profits can be attained. A naive buy and hold strategy did not yield an economically significant performance, either.

6.2 Trading strategy based on interval forecasts

To evaluate the economic significance of the constructed interval forecasts, the following trading rule is used:

$$\text{If } IV_{t-1} < (>) \frac{U_{t/t-1}(\alpha) + L_{t/t-1}(\alpha)}{2}, \text{ then go long (short).}$$

$$\text{If } IV_{t-1} = \frac{U_{t/t-1}(\alpha) + L_{t/t-1}(\alpha)}{2}, \text{ then do nothing.}$$

The rational is that in the case where the value of the volatility index is closer to the lower (upper) bound of the next day's forecast interval, the index price is expected to increase and a long (short) position is taken in the volatility futures. Notice that the criterion requires a contemporaneous comparison of the volatility index value and the constructed intervals at time (*t*-1); this is in contrast to Christoffersen's test.[11]

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[10] A_p is used since the distribution of the returns of the futures trading strategy is found to be non-normal. It is calculated by using the S&P 500 and the DJIA indices to proxy the benchmark (market) portfolio in the VIX and VXD futures strategies, respectively. To check the sensitivity of the results on A_p to the choice of the benchmark portfolio, the VIX and VXD indices were also used to proxy the market portfolio; the results did not change.

[11] We have also considered implementing an alternative trading strategy where trades would be triggered only when the implied volatility index crosses the limits of the constructed interval forecast. Again, a

Table 2.10 shows the annualised *SR* and A_p, and their corresponding bootstrapped 95% confidence intervals obtained for each one of the three shortest VIX and VXD futures series. Results are reported for the interval forecasts derived by the economic variables (Panel A), AR(1) (Panel B), VAR (Panel C), PCA (Panel D), ARIMA(1,1,1) (Panel E) and the ARFIMA(1,*d*,1) (Panel F) models. We can see that the obtained *SR* and A_p are statistically insignificant for all VIX and VXD futures series and for all six models; the same results hold for a naive buy and hold strategy. Therefore, no economically significant profits can be obtained just as was the case with the trading strategy based on point forecasts.

7. Robustness of results

The robustness of the results presented in Sections 5 and 6 is investigated. First, the sensitivity of the statistical and economic significance of the constructed point and interval forecasts across various sub-periods is explored. Second, the effect of transaction costs on the profitability of transaction costs is examined.

The robustness of the reported results across various sub-periods is assessed by a recursive "pseudo" out-of-sample scheme [see also Gonçalves and Guidolin (2006), for a similar approach]. First, the sample from Feb 2, 2001-Mar 17, 2005 is used to form forecasts for the observations over the next 100 observations (first out-of-sample period). Second, 100 observations are added to the initial sample and forecasts are generated for the next 100 observations (second out-of-sample period) and so forth. Overall, six out-of-sample periods were formed. All models are re-estimated at each time step (i.e. daily).

With respect to the statistical evaluation of the constructed forecasts, Table 2.11 shows the frequency of cases where the random walk is beaten (Panel A) and the null hypothesis in Christoffersen's test is accepted for each sub-period (Panel B). In the case of the point forecasts, we can see that the random walk is outperformed in more than 5% of the cases for each sub-sample. Similar are the findings for the interval forecasts, where the null hypothesis in Christoffersen's test is accepted in more than 5% of the cases for each sub-period. These findings suggest that a statistically predictable pattern exists in the

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contemporaneous comparison of the volatility index value and the constructed interval forecast is required. However, this rule did not trigger any trades since the value of the volatility index did not cross the bounds of the interval forecast through our sample.

dynamics of implied volatility indices for all sub-samples at a 5% level of significance and by assuming independence.

Regarding economic significance of the constructed forecasts, Tables 2.12 and 2.13 show the annualised Sharpe ratio (Panel A), Leland's alpha (Panel B) and their bootstraped 95% confidence intervals for the trading strategies with the VIX and VXD shortest series that are based on point and interval forecasts, respectively. Results are reported for each sub-sample. We can see that *SR* and A_p are statistically insignificant in almost all cases and hence, no economically significant profits can be obtained in any sub-period. This holds for the trading strategies based on point forecasts as well as for those based on interval forecasts.

A further robustness check is conducted by implementing the trading strategies without taking into account the CBOE transaction costs. This is because the insignificance of the profits attained by the employed trading strategies might be due to huge transaction costs that distort the reported results. However, in the case where the transaction costs are ignored, the Sharpe ratio and Leland alpha do not differ materially compared with the ones that are reported in Section 6.

Overall, the "pseudo" out-of-sample scheme confirmed that the results reported in Section 5 and 6 are robust across sub-samples. In particular, predictability of implied volatility indices in the statistical sense is documented; however, the trading games did not deliver any abnormal profits and hence, the results are not economically significant. Furthermore, the results pertinent to the profitability of the trading strategies are robust to the inclusion of transaction costs.

8. Conclusions

This paper has contributed to the literature on whether the evolution of implied volatility can be forecasted in the equity markets by using a number of European and U.S. implied volatility indices. To this end, six alternative model specifications (economic variables, AR(1), VAR, PCA, ARIMA and ARFIMA models) have been employed to generate point as well as interval forecasts. The accuracy of the generated out-of-sample forecasts was evaluated both in a statistical and economic setting. The economic significance was assessed by employing for the first time trading strategies with the VIX and VXD volatility futures.

We found that both the point and interval forecasts are statistically significant. The evidence on the predictability of the point forecasts is stronger for the European indices where the VAR and PCA models perform best among the competing models. In the case of the interval forecasts, the predictable pattern is stronger for the U.S. indices; the VAR model performs best. However, the generated point and interval forecasts are not economically significant.

These results have at least three implications. First, the previous literature that had considered only point forecasts is extended in that it is found that implied volatility can be statistically predicted in both a point and interval forecast setting. Second, the presence of implied volatility spillover effects between the various markets is also confirmed. Finally, the results indicate that the newly CBOE volatility futures markets are informational efficient just as other derivative markets. Given that the answer on the predictability question always depends on the assumed specification of the predictive regression, alternative model specifications should be considered [see e.g., Welch and Goyal (2008)]. Also longer horizons can be examined. In the interests of brevity, these topics are best left for future research.

Panel A: Summary Statistics for Implied Volatility Indices (Levels): Feb 2, 2001 to Mar 17, 2005							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX_NEW**	**VCAC**	**VSTOXX**
Mean	0.22	0.21	0.37	0.21	0.29	0.26	0.28
Std. Deviation	0.07	0.07	0.14	0.07	0.12	0.10	0.11
Skewness	0.75	0.67	0.30	0.69	0.82	1.04	0.91
Kurtosis	2.93	2.74	1.90	2.68	2.75	3.47	2.97
ρ_1	0.95*	0.96*	0.96*	0.96*	0.98*	0.98*	0.97*
ADF	-3.18	-2.91	-2.30	-2.34	-2.12	-2.14	-2.32

Panel B: Summary Statistics for Implied Volatility Indices (Daily Differences): Feb 2, 2001 to Mar 17, 2005							
Mean	-0.0004	-0.0004	-0.0008	-0.0003	-0.0002	-0.0001	-0.0002
Std. Deviation	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Skewness	0.05	0.17	-0.24	0.33	0.82	1.79	1.4
Kurtosis	5.29	6.02	6.02	6.92	10.47	16.44	18.09
ρ_1	0.01	-0.03	0.05	0.03	-0.02	-0.03	-0.03
ADF	-15.37*	-32.01*	-29.26*	-30.40*	-32.26*	-32.79*	-24.51*

Panel C: Summary Statistics for VIX Futures: Mar 18, 2005 to Sep 28, 2007						
	Levels			**Daily Differences**		
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
# Observations	630	608	590			
Mean	142.28	148.90	154.79	0.00	0.00	0.00
Std. Deviation	29.30	23.86	20.00	0.04	0.03	0.02
Skewness	2.37	2.15	1.90	0.83	0.99	0.56
Kurtosis	9.23	8.01	6.92	14.25	8.30	8.21
ρ_1	0.99*	0.98*	0.95*	-0.01	-0.02	-0.06
Average Volume	699.57	367.06	333.14			
(min-max)	*(5-9,139)*	*(5-4,683)*	*(5-5,072)*			

Panel D: Summary Statistics for VXD Futures: Mar 18, 2005 to Sep 28, 2007						
	Levels			**Daily Differences**		
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
# Observations	490	370	290			
Mean	136.78	144.52	151.59	0.00	0.00	0.00
Std. Deviation	30.24	26.58	22.93	0.05	0.03	0.03
Skewness	2.01	1.58	1.28	0.78	0.77	0.25
Kurtosis	7.12	5.04	3.92	11.32	7.99	8.22
ρ_1	0.91*	0.84*	0.79*	-0.03	0.03	-0.06
Average Volume	63.75	38.83	38.4			
(min-max)	*(5-328)*	*(5-308)*	*(5-336)*			

Table 2.1: Summary statistics. Entries report the summary statistics of each one of the implied volatility indices in the levels and the first daily differences. The first order autocorrelation ρ1, the Jarque-Bera and the Augmented Dickey Fuller (ADF) (an intercept has been included in the test equation) test values are also reported. One asterisk denotes rejection of the null hypothesis at the 1% level. The null hypothesis for the Jarque-Bera and the ADF tests is that the series is normally distributed and has a unit root, respectively. Summary statistics for the VIX and VXD futures in levels and changes are also provided.

	ΔVIX_t	$\Delta VXOA_t$	ΔVXN_t	ΔVXD_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
Included Obs.	954	955	953	950	1015	1017	1015
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
c_1	0.000	0.000	-0.001	0.000	-0.001	0.000	0.000
	(0.556)	*(0.041)*	*(-0.822)*	*(-0.220)*	*(-0.772)*	*(-0.327)*	*(0.261)*
R_{t-1}^{+}	-0.020	-0.027	-0.064	-0.105	0.009	**-0.164****	0.002
	(-0.215)	*(-0.596)*	*(-1.452)*	*(-1.612)*	*(0.117)*	*(-2.417)*	*(0.022)*
R_{t-1}^{-}	0.147	0.050	-0.018	-0.046	-0.054	-0.184	0.054
	(1.099)	*(0.407)*	*(-0.281)*	*(-0.437)*	*(-0.528)*	*(-1.814)*	*(0.433)*
i_{t-1}	-0.020	-0.020	-0.054	-0.056	-0.075	0.012	-0.078
	(-0.375)	*(-0.366)*	*(-1.054)*	*(-1.378)*	*(-0.599)*	*(0.121)*	*(-0.697)*
fx_{t-1}	-0.084	-0.074	-0.018	-0.055	0.124	0.088	0.185
	(-1.184)	*(-1.009)*	*(-0.195)*	*(-0.894)*	*(1.230)*	*(0.854)*	*(1.796)*
oil_{t-1}	0.020	-0.007	0.022	-0.009	-0.005	-0.024	-0.017
	(1.227)	*(-0.475)*	*(1.09)*	*(-0.537)*	*(-0.230)*	*(-1.401)*	*(-0.770)*
ΔHV_{t-1}	0.107	0.025	**0.092****	0.086	0.034	**0.131****	0.049
	(1.407)	*(0.366)*	*(2.151)*	*(1.464)*	*(0.517)*	*(1.984)*	*(0.477)*
ΔIV_{t-1}	0.072	-0.019	0.014	-0.036	-0.043	**-0.144***	-0.004
	(0.753)	*(-0.201)*	*(0.269)*	*(-0.516)*	*(-0.516)*	*(-3.151)*	*(-0.037)*
Δys_{t-1}	0.009	0.007	0.004	0.004	-0.018	-0.009	-0.013
	(1.428)	*(1.135)*	*(0.512)*	*(0.699)*	*(-1.160)*	*(-0.694)*	*(-0.779)*
vol_{t-1}	-0.001	-	0.001	0.000	-0.001	0.000	0.000
	(-0.927)	-	*(0.443)*	*(0.476)*	*(-0.366)*	*(0.027)*	*(-0.185)*
Adj.R-sq.	**0.002**	**-0.004**	**0.006**	**0.004**	**-0.004**	**0.025**	**-0.003**

Table 2.2: Forecasting with the economic variables model. The entries report results from the regression of each implied volatility index on a set of lagged economic variables, augmented by an AR(1) term. The following specification is estimated:

$$\Delta IV_t = c_1 + a_1^+ R_{t-1}^+ + a_1^- R_{t-1}^- + \beta_1 i_{t-1} + \gamma_1 fx_{t-1} + \delta_1 oil_{t-1} + \zeta_1 \Delta HV_{t-1} + \rho_1 \Delta IV_{t-1} + \kappa_1 \Delta ys_{t-1} + \xi_1 vol_{t-1} + \varepsilon_t$$

where *ΔIV*: the changes of the implied volatility index, R_{t-1}^{+}: the underlying positive stock index return, R_{t-1}^{-}: the underlying negative stock index return, *i*: the one-month interbank/Euribor interest rate for the US/European market, log-differenced, *fx*: the EUR/USD exchange rate log-differenced, *oil*: WTI/Brent crude oil price for the American/European market, in log-differences, *HV*: the 30-days historical volatility, *Δys*: the changes of the yield spread calculated as the difference between the yield of the 10-year government bond and the one-month interbank interest rate, and *vol*: the volume in log-differences of the futures contract of the underlying index. The estimated coefficients, Newey-West *t*-statistics in parentheses, and the adjusted R2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The model has been estimated for the period February 2, 2001 to March 17, 2005.

	ΔVIX_t	$\Delta VXOA_t$	ΔVXN_t	ΔVXD_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
Panel A: AR(1) Model							
Included Obs.	956	955	953	956	1015	1017	1015
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
c_1	0.000	0.000	**-0.001****	0.000	0.000	0.000	0.000
	(-1.104)	*(-1.203)*	*(-2.082)*	*(-1.127)*	*(-0.315)*	*(-0.178)*	*(-0.233)*
ΔIV_{t-1}	0.008	-0.026	0.052	0.025	-0.016	-0.029	-0.029
	(0.169)	*(-0.545)*	*(1.386)*	*(0.590)*	*(-0.435)*	*(-0.777)*	*(-0.539)*
Adj.R-sq.	**-0.001**	**0.000**	**0.002**	**0.000**	**-0.001**	**0.000**	**0.000**

	ΔVIX_t	$\Delta VXOA_t$	ΔVXN_t	ΔVXD_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
Panel B: VAR Model							
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
ΔVIX_{t-1}	0.158	**0.478***	0.206	**0.316***	**0.459***	0.211	**0.383***
	(1.694)	*(5.203)*	*(1.890)*	*(3.953)*	*(3.900)*	*(1.903)*	*(3.119)*
$\Delta VXOA_{t-1}$	-0.038	**-0.394***	-0.085	0.051	-0.014	0.112	0.055
	(-0.462)	*(-4.881)*	*(-0.891)*	*(0.729)*	*(-0.138)*	*(1.147)*	*(0.508)*
ΔVXN_{t-1}	-0.049	-0.045	-0.063	-0.028	**-0.113****	-0.044	-0.079
	(-1.235)	*(-1.148)*	*(-1.374)*	*(-0.826)*	*(-2.275)*	*(-0.936)*	*(-1.514)*
ΔVXD_{t-1}	-0.070	-0.038	0.118	**-0.283***	-0.017	**-0.199****	0.099
	(-0.925)	*(-0.507)*	*(1.342)*	*(-4.361)*	*(-0.176)*	*(-2.225)*	*(0.994)*
$\Delta VDAX\_New_{t-1}$	-0.007	0.005	-0.009	-0.042	**-0.298***	0.066	0.033
	(-0.128)	*(0.101)*	*(-0.143)*	*(-0.919)*	*(-4.431)*	*(1.039)*	*(0.466)*
$\Delta VCAC_{t-1}$	**-0.108***	**-0.116***	**-0.098***	-0.050	-0.064	**-0.237***	**-0.113***
	(-3.349)	*(-3.669)*	*(-2.630)*	*(-1.833)*	*(-1.587)*	*(-6.216)*	*(-2.683)*
$\Delta VSTOXX_{t-1}$	0.028	0.027	0.032	0.043	**0.196***	**0.259***	**-0.130****
	(0.566)	*(0.560)*	*(0.572)*	*(1.035)*	*(3.187)*	*(4.482)*	*(-2.037)*
C	0.000	0.000	-0.001	0.000	0.000	0.000	0.000
	(-0.903)	*(-0.957)*	*(-1.867)*	*(-0.776)*	*(-0.609)*	*(-0.066)*	*(-0.640)*
Adj. R^2	**0.012**	**0.037**	**0.021**	**0.043**	**0.063**	**0.117**	**0.084**

Table 2.3: Forecasting with the univariate autoregressive and VAR models. Panel A: The entries report results from the estimation of a univariate AR(1) specification for the daily changes ΔIV of each implied volatility index, i.e. $\Delta IV_t = c_1 + \lambda_1 \Delta IV_{t-1} + \varepsilon_t$. **Panel B:** The entries report the estimated coefficients of a VAR, for the set of the seven implied volatility (IV) indices: $Y_t = C + \Phi_1 Y_{t-1} + \varepsilon_t$, where Y_t is the (7x1) vector of IV indices (in differences), C is a (7x1) vector of constants, Φ_1 is the (7x7) matrix of coefficients to be estimated, and u_t is a (7x1) vector of errors. The estimated coefficients, Newey-West *t*-statistics in parentheses and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The models have been estimated for the period February 2, 2001 to March 17, 2005.

Panel A: Amount of Variance Explained by PCs				
	PC1	**PC2**	**PC3**	**PC4**
Variance Explained (%)	64.32%	16.71%	6.99%	6.03%
Cumulative Variance Explained (%)	64.32%	81.03%	88.02%	94.05%

Panel B: Pairwise Correlations of PCs and Economic Variables				
	PC1	**PC2**	**PC3**	**PC4**
$R_{S\&P\,500}$	0.77	-0.26	0.01	0.14
$R_{S\&P\,100}$	0.76	-0.27	0.01	0.14
$R_{NAS\,100}$	0.64	-0.25	0.11	0.01
R_{DJIA}	0.75	-0.24	-0.02	0.15
R_{DAX}	0.72	0.24	-0.22	-0.02
R_{CAC}	0.67	0.35	-0.16	0.02
R_{STOXX}	0.70	0.33	-0.19	-0.01
i_{US}	-0.02	-0.01	0.02	-0.02
i_{EU}	-0.02	-0.02	0.01	-0.03
fx	0.00	-0.02	0.01	-0.03
o_{WTI}	-0.01	0.01	0.00	0.02
o_{BRENT}	-0.02	0.01	0.00	0.01
$vol_{S\&P\,500}$	-0.12	-0.06	0.06	0.00
$vol_{NAS\,100}$	-0.07	-0.06	0.06	0.00
vol_{DJIA}	-0.11	-0.09	0.06	-0.02
vol_{DAX}	-0.09	-0.08	0.02	0.00
vol_{CAC}	-0.03	-0.04	-0.07	-0.03
vol_{STOXX}	-0.07	-0.08	0.02	-0.01

Table 2.4: Variance explained (%) by the PCs and correlation of the PCs and the economic variables: PCA has been applied on the daily changes of implied volatility indices for the period February 2, 2001 to March 17, 2005. **Panel A** reports the amount of variance explained (%) by the first four PCs (i.e. PC1, PC2, PC3 and PC4) of the changes of the implied volatility indices. **Panel B** presents the contemporaneous correlations of the PCs with the economic variables employed in equation (2.1), namely the return on S&P 500 ($R_{S\&P500}$), S&P 100 ($R_{S\&P100}$), NASDAQ 100 (R_{NAS100}), DJIA (R_{DJIA}), DAX 30 (R_{DAX}), CAC 40 (R_{CAC}) and DJ EURO-STOXX 50 (R_{STOXX}), the one U.S. interbank (i_{US}) and Euribor (i_{EU}) interest rate, the Euro/USD exchange rate (fx), the WTI (o_{WTI}) and Brent Crude Oil (o_{BRENT}) prices, and the volume of the futures contract on S&P 500 ($vol_{S\&P500}$), NASDAQ 100 (vol_{NAS100}), DJIA (vol_{DJIA}), DAX 30 (vol_{DAX}), CAC 40 (vol_{CAC}) and DJ EURO-STOXX 50 (vol_{STOXX}).

	ΔVIX$_t$	ΔVXOA$_t$	ΔVXN$_t$	ΔVXD$_t$	ΔVDAX-New$_t$	ΔVCAC$_t$	ΔVSTOXX$_t$
Included Obs.	932	931	931	932	950	953	949
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
c	0.000	0.000	**-0.001****	0.000	0.000	0.000	0.000
	(-0.972)	*(-1.106)*	*(-2.068)*	*(-1.084)*	*(-0.668)*	*(-0.299)*	*(-0.522)*
PC1$_{t-1}$	0.000	0.000	**-0.001****	-0.001	-0.002	**-0.004***	**-0.003***
	(0.810)	*(0.462)*	*(-2.460)*	*(-1.454)*	*(-2.820)*	*(-5.567)*	*(-3.992)*
PC2$_{t-1}$	**0.001****	0.001	**0.001****	**0.001***	0.002	0.001	**0.004***
	(2.070)	*(1.773)*	*(2.374)*	*(2.719)*	*(3.610)*	*(1.082)*	*(5.164)*
PC3$_{t-1}$	0.001	0.001	0.001	0.001	0.001	**0.004***	0.001
	(1.880)	*(1.516)*	*(1.683)*	*(1.126)*	*(0.848)*	*(6.167)*	*(1.037)*
PC4$_{t-1}$	0.000	0.000	-0.001	0.000	-0.002	0.001	**-0.001****
	(-0.231)	*(0.191)*	*(-0.782)*	*(-0.750)*	*(-2.554)*	*(1.298)*	*(-2.159)*
Adj. R^2	**0.012**	**0.007**	**0.020**	**0.015**	**0.036**	**0.112**	**0.068**

Table 2.5: Forecasting with the PCA model. The entries report results from the regression $\Delta IV_t = c_1 + r_{1j}PC1_{t-1} + r_{2j}PC2_{t-1} + r_{3j}PC3_{t-1} + r_{4j}PC4_{t-1} + \varepsilon_t$ of the changes *ΔIV* of each implied volatility index on the lagged first four principal components *PC*1, *PC*2, *PC*3 and *PC*4 derived from the set of the seven IV indices. The estimated coefficients, Newey-West *t*-statistics in parentheses, and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The model has been estimated for the period February 2, 2001 to March 17, 2005.

Panel A: ARIMA(1,1,1) Model							
	ΔVIX_t	$\Delta VXOA_t$	ΔVXN_t	ΔVXD_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
Included Obs.	994	993	992	994	1030	1033	1030
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
c	0.000	0.000	-0.001**	0.000	0.000	0.000	0.000
	(-1.209)	*(-1.612)*	*(-1.963)*	*(-0.911)*	*(-0.474)*	*(-0.209)*	*(-0.399)*
φ	0.735*	-0.773*	0.703*	0.534	-0.879*	0.629	-0.856*
	(2.590)	*(-5.989)*	*(4.921)*	*(1.014)*	*(-8.333)*	*(1.323)*	*(-6.790)*
θ	0.774*	-0.848*	0.773*	0.574	-0.909*	0.588	-0.898*
	(2.935)	*(-7.352)*	*(6.076)*	*(1.133)*	*(-9.448)*	*(1.204)*	*(-8.251)*
Adj. R^2	0.001	0.012	0.009	0.000	0.002	0.001	0.004

Panel B: ARFIMA (1,*d*,1) Model							
	ΔVIX_t	$\Delta VXOA_t$	ΔVXN_t	ΔVXD_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
Included Obs.	995	994	993	995	1031	1034	1031
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
d	-0.210*	-0.178*	-0.071**	-0.169*	-0.078**	-0.031	-0.091*
	(-3.725)	*(-3.459)*	*(-2.112)*	*(-2.996)*	*(-2.269)*	*(-1.002)*	*(-2.974)*
φ	-0.172	-0.121	0.622*	-0.177	0.366	0.667*	0.627*
	(-0.831)	*(-0.511)*	*(5.009)*	*(-0.822)*	*(1.326)*	*(3.317)*	*(3.152)*
θ	0.033	0.021	0.723*	0.011	0.431	0.641*	0.688*
	(0.190)	*(0.099)*	*(6.993)*	*(0.058)*	*(1.677)*	*(3.080)*	*(3.818)*
Adj. R^2	0.016	0.012	0.010	0.011	0.003	0.002	0.008

Table 2.6: Forecasting with the ARIMA(1,1,1) and the ARFIMA(1,*d*,1) models. Panel A: The entries report results from the estimation of an ARIMA(1, 1, 1) model. The specification $(1+\phi L)\Delta IV_t = c + (1+\theta L)\varepsilon_t$ is used. **Panel B:** The entries report the results from the estimation of an ARFIMA(1, *d*, 1) model. The specification $(1+\varphi L)(1-L)^d(\Delta IV_t - \mu) = (1+\theta L)\varepsilon_t$ is used. The estimated coefficients, *t*-statistics in parentheses, and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The models have been estimated for the period February 2, 2001 to March 17, 2005.

	VIX	VXOA	VXN	VXD	VDAX New	VCAC	VSTOXX
Panel A: Random Walk							
RMSE	1.07	1.01	1.03	1.01	0.94	1.04	1.00
MAE	0.68	0.64	0.70	0.64	0.67	0.71	0.70
Panel B: Regression Model Based on Economic Variables							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX New**	**VCAC**	**VSTOXX**
RMSE	1.08	1.02	1.04	1.00	0.94	1.05	1.01
MAE	0.67	0.63	0.70	0.63	**0.67****	0.72	0.70
MCP	**54.71%****	50.67%	53.70%	49.50%	**55.31%***	47.05%	49.84%
Panel C: AR(1) Model							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX New**	**VCAC**	**VSTOXX**
RMSE	1.07	1.01	1.04	1.01	0.94	1.04	1.01
MAE	0.67	**0.63****	0.70	0.63	0.68	0.71	0.70
MCP	52.86%	53.20%	**56.06%***	52.36%	50.24%	52.47%	49.21%
Panel D: VAR Model							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX New**	**VCAC**	**VSTOXX**
RMSE	1.07	1.01	1.06	0.99	**0.85***	**0.99***	**0.89***
MAE	0.68	0.63	0.70	0.63	**0.62***	**0.68***	**0.65***
MCP	51.54%	**55.65%***	52.74%	52.06%	**61.20%***	**58.22%***	**60.43%***
Panel E: PCA Model							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX New**	**VCAC**	**VSTOXX**
RMSE	1.08	1.02	1.05	1.01	**0.85***	**0.99***	**0.90***
MAE	0.68	0.64	0.70	0.64	**0.62***	**0.69***	**0.65***
MCP	52.91%	53.25%	50.34%	50.00%	**59.87%***	**58.56%***	**58.43%***
Panel F: ARIMA(1,1,1) Model							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX New**	**VCAC**	**VSTOXX**
RMSE	1.07	**1.00****	1.04	1.00	0.94	1.04	1.03
MAE	0.67	**0.63****	0.70	0.63	0.67	0.71	0.71
MCP	53.20%	**56.23%***	49.83%	49.66%	53.09%	53.27%	52.05%
Panel G: ARFIMA(1,*d*,1) Model							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX New**	**VCAC**	**VSTOXX**
RMSE	1.06	1.00	1.03	1.01	0.94	1.04	1.00
MAE	0.67	**0.63***	**0.68****	0.64	0.67	0.70	0.69
MCP	**53.41%****	**55.36%***	**56.49%***	**53.90%****	**54.38%****	**53.53%****	52.96%

Table 2.7: Out-of-sample performance of the model specifications for each one of the implied volatility indices. The root mean squared prediction error (RMSE), the mean absolute prediction error (MAE), and the mean correct prediction (MCP) of the direction of change in the value of the implied volatility index are reported. The random walk model (Panel A), economic variables model (Panel B), AR(1) model (Panel C), VAR model (Panel D), PCA model (Panel E), ARIMA(1,1,1) model (Panel F) and the ARFIMA(1,*d*,1) model (Panel G) have been implemented. The null hypothesis is that the random walk and the model under consideration perform equally well, against the alternative that the model under consideration performs better, have been tested via the Modified Diebold-Mariano test (for RMSE and MAE) and the ratio test (for MCP). One and two asterisks denote rejection of the null hypothesis at 1% and 5% significance levels, respectively. The models have been estimated recursively for the period March 18, 2005 to September 28, 2007.

	VIX	VXOA	VXN	VXD	VDAX_New	VCAC	VSTOXX
Panel A: Economic Variables Model Interval Forecasts							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX_New**	**VCAC**	**VSTOXX**
# Violations	6.23%	5.22%	2.69%	6.40%	1.43%	3.51%	3.34%
*LR*unc	1.76	0.06	7.94*	2.25	23.36*	3.26	4.12**
Panel B: AR(1) Interval Forecasts							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX_New**	**VCAC**	**VSTOXX**
# Violations	6.06%	5.22%	2.86%	6.90%	1.43%	2.87%	1.26%
*LR*unc	1.32	0.06	**6.71***	**4.07****	**23.36***	**7.02***	**26.29***
Panel C: VAR Interval Forecasts							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX_New**	**VCAC**	**VSTOXX**
# Violations	5.99%	5.65%	3.77%	6.34%	1.17%	3.52%	1.17%
*LR*unc	1.14	0.50	2.04	2.03	26.38*	3.04	26.46*
Panel D: PCA Interval Forecasts							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX_New**	**VCAC**	**VSTOXX**
# Violations	6.16%	5.48%	3.42%	7.02%	1.00%	3.36%	1.00%
*LR*unc	1.56	0.27	3.41	**4.48****	**29.52***	**3.82****	**29.60***
Panel E: ARIMA(1,1,1) Interval Forecasts							
	VIX	**VXOA**	**VXN**	**VXD**	**VDAX_New**	**VCAC**	**VSTOXX**
# Violations	7.24%	6.56%	4.38%	8.59%	1.74%	3.51%	1.89%
LRunc	**5.54****	2.80	0.51	**13.36***	**18.62***	3.26	**16.72***
Panel F: ARFIMA(1,*d*,1) Interval Forecasts							
	VIX	**VXOA**	**VXN**	**VXD**	VDAX_New	**VCAC**	**VSTOXX**
# Violations	5.52%	5.36%	2.92%	6.49%	1.41%	2.83%	1.56%
*LR*unc	0.34	0.16	6.54*	2.65	24.03*	**7.47***	**21.67***

Table 2.8: Statistical accuracy of the interval forecasts. Entries report the percentage of the observations that fall outside the constructed intervals, and the values of Christoffersen's (1998) likelihood ratio test of unconditional coverage (LR_{unc}) for each implied volatility index. The null hypothesis is that the percentage of times that the actually realized index value falls outside the constructed α%-intervals is a %. One and two asterisks denote rejection of the null hypothesis at 1% and 5% significance levels, respectively. The results are reported for daily 5%-interval forecasts over the period March 18, 2005 to September 28, 2007 generated by the economic variables model (Panel A), AR(1) model (Panel B), VAR model (Panel C), PCA model (Panel D), ARIMA(1,1,1) model (Panel E) and ARFIMA (1,*d*,1) model (Panel F).

	VIX			VXD		
Panel A: Economic Variables Model Point Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	0.0306	0.0175	0.0062	-0.0176	-0.0787	-0.1081
95% CI	*(-0.05, 0.11)*	*(-0.06, 0.10)*	*(-0.08, 0.09)*	*(-0.11, 0.08)*	*(-0.19, 0.04)*	*(-0.26, 0.03)*
A_p	0.2487	0.1026	0.0347	-0.3606	-0.7400	-0.7774
95% CI	*(-0.51, 1.00)*	*(-0.45, 0.67)*	*(-0.49, 0.53)*	*(-1.41, 0.66)*	*(-1.82,0.28)*	*(-1.90, 0.28)*
Panel B: AR(1) Point Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0190	-0.0392	-0.0366	-0.0680	-0.0654	-0.1234
95% CI	*(-0.10, 0.06)*	*(-0.12, 0.04)*	*(-0.12, 0.05)*	*(-0.15, 0.03)*	*(-0.18, 0.06)*	*(-0.25, 0.02)*
A_p	-0.3375	-0.3367	-0.2385	**-1.1944***	-0.6825	-0.8191
95% CI	*(-0.96, 0.25)*	*(-0.81, 0.13)*	*(-0.67, 0.19)*	*(-2.13, -0.34)*	*(-1.55, 0.14)*	*(-1.84, 0.11)*
Panel C: VAR Point Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0140	-0.0186	-0.0369	0.0812	-0.0209	0.0071
95% CI	*(-0.09, 0.06)*	*(-0.10, 0.06)*	*(-0.12, 0.05)*	*(-0.02, 0.17)*	*(-0.15, 0.10)*	*(-0.15, 0.14)*
A_p	-0.2098	-0.1626	-0.2377	0.8104	-0.2192	0.0825
95% CI	*(-0.93, 0.52)*	*(-0.71, 0.40)*	*(-0.74, 0.26)*	*(-0.27, 1.95)*	*(-1.30, 0.94)*	*(-0.96, 1.20)*
Panel D: PCA Point Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0664	-0.0596	-0.0828	**0.1137***	0.0746	0.0773
95% CI	*(-0.14, 0.01)*	*(-0.14, 0.02)*	*(-0.16, 0.00)*	*(0.02, 0.21)*	*(-0.05, 0.19)*	*(-0.06, 0.22)*
A_p	-0.6747	-0.4272	-0.5023	**1.1268***	0.6274	0.5529
95% CI	*(-1.42, 0.06)*	*(-1.00, 0.14)*	*(-0.99, 0.00)*	*(0.06, 2.25)*	*(-0.41, 1.77)*	*(-0.48, 1.64)*
Panel E: ARIMA(1,1,1) Point Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	0.0101	0.0202	0.0274	0.0571	0.0373	-0.0214
95% CI	*(-0.07, 0.09)*	*(-0.06, 0.10)*	*(-0.06, 0.11)*	*(-0.04, 0.15)*	*(-0.09, 0.16)*	*(-0.16, 0.12)*
A_p	0.0612	0.1211	0.1527	0.6021	0.3201	-0.1464
95% CI	*(-0.66, 0.81)*	*(-0.44, 0.69)*	*(-0.35, 0.65)*	*(-0.48, 1.71)*	*(-0.76, 1.43)*	*(-1.22, 0.88)*
Panel F: ARFIMA(1,*d*,1) Point Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0127	-0.0286	-0.0268	0.0494	-0.0133	0.1220
95% CI	*(-0.09, 0.07)*	*(-0.11, 0.05)*	*(-0.11, 0.06)*	*(-0.05, 0.15)*	*(-0.13, 0.11)*	*(-0.02, 0.26)*
A_p	-0.2471	-0.2528	-0.1752	0.3651	-0.1755	0.9140
95% CI	*(-0.91, 0.40)*	*(-0.75, 0.24)*	*(-0.63, 0.27)*	*(-0.65, 1.37)*	*(-1.20, 0.82)*	*(-0.09, 1.92)*

Table 2.9: Trading strategy with VIX /VXD futures based on point forecasts from March 18, 2005 to September 28, 2007. The entries show the annualised Sharpe ratio and Leland's Alpha (A_p) and their respective bootstrapped 95% confidence intervals Grünbichler and Longstaff). The strategy is based on point forecasts obtained from the economic variables model (Panel A), AR(1) model (Panel B), VAR model (Panel C), PCA model (Panel D), ARIMA(1,1,1) model (Panel E), and ARFIMA(1,*d*,1) model (Panel F). The Sharpe ratio for the S&P 500 and the Dow Jones Industrial Average is 0.0265 [95% CI = (-0.05, 0.10)] and 0.0319 [95% CI = (-0.04, 0.11)], respectively. One asterisk denotes rejection of the null hypothesis of a zero Sharpe ratio (A_p) at a 5% level of significance.

	VIX			VXD		
Panel A: Economic Variables Model Interval Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	0.0029	-0.0098	-0.0284	0.0144	-0.0409	-0.0872
95% CI	*(-0.08, 0.08)*	*(-0.09, 0.07)*	*(-0.11, 0.06)*	*(-0.08, 0.11)*	*(-0.16, 0.08)*	*(-0.23, 0.05)*
A_p	-0.0092	-0.0827	-0.1705	-0.0154	-0.4002	-0.6389
95% CI	*(-0.75, 0.74)*	*(-0.65, 0.47)*	*(-0.69, 0.34)*	*(-1.07, 1.05)*	*(-1.47, 0.63)*	*(-1.77, 0.41)*
Panel B: AR(1) Interval Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0450	-0.0751	-0.0714	-0.0411	-0.0269	-0.0345
95% CI	*(-0.12, 0.03)*	*(-0.15, 0.01)*	*(-0.15, 0.01)*	*(-0.13, 0.06)*	*(-0.14, 0.10)*	*(-0.18, 0.11)*
A_p	-0.5678	-0.5776	-0.4402	-0.8593	-0.3295	-0.1765
95% CI	*(-1.21, 0.04)*	*(-1.06, -0.10)*	*(-0.89, 0.00)*	*(-1.84, 0.06)*	*(-1.25, 0.55)*	*(-1.15, 0.84)*
Panel C: VAR Interval Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0324	-0.0394	-0.0675	0.0316	0.0018	0.0258
95% CI	*(-0.11, 0.04)*	*(-0.12, 0.04)*	*(-0.15, 0.02)*	*(-0.07, 0.13)*	*(-0.12, 0.12)*	*(-0.12, 0.16)*
A_p	-0.4023	-0.3095	-0.4172	0.2681	-0.0048	0.2070
95% CI	*(-1.13, 0.31)*	*(-0.86, 0.24)*	*(-0.92, 0.09)*	*(-0.82, 1.41)*	*(-1.07, 1.13)*	*(-0.85, 1.33)*
Panel D: PCA Interval Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0375	-0.0385	-0.0791	0.0644	0.0817	0.0821
95% CI	*(-0.11, 0.04)*	*(-0.12, 0.04)*	*(-0.16, 0.01)*	*(-0.03, 0.16)*	*(-0.04, 0.20)*	*(-0.06, 0.23)*
A_p	-0.3954	-0.2837	-0.4830	0.5768	0.7058	0.5770
95% CI	*(-1.15, 0.35)*	*(-0.85, 0.27)*	*(-0.99, 0.03)*	*(-0.50, 1.67)*	*(-0.38, 1.18)*	*(-0.48, 1.61)*
Panel E: ARIMA(1,1,1) Interval Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	0.0177	0.0491	0.0439	0.0659	0.0495	-0.0323
95% CI	*(-0.07, 0.09)*	*(-0.03, 0.13)*	*(-0.04, 0.13)*	*(-0.03, 0.16)*	*(-0.07, 0.17)*	*(-0.18, 0.11)*
A_p	0.1823	0.5480	0.2522	0.7467	0.4476	-0.2393
95% CI	*(-0.54, 0.96)*	*(-0.22, 0.90)*	*(-0.24, 0.76)*	*(-0.32, 1.85)*	*(-0.64, 1.55)*	*(-1.35, 0.80)*
Panel F: ARFIMA(1,*d*,1) Interval Forecasts						
	Shortest	**2nd Shortest**	**3rd Shortest**	**Shortest**	**2nd Shortest**	**3rd Shortest**
Sharpe Ratio	-0.0230	-0.0386	-0.0354	0.0209	-0.0405	0.1107
95% CI	*(-0.10, 0.06)*	*(-0.12, 0.04)*	*(-0.12, 0.05)*	*(-0.07, 0.12)*	*(-0.16, 0.08)*	*(-0.03, 0.25)*
A_p	-0.3425	-0.3228	-0.2251	-0.0366	-0.4248	0.8353
95% CI	*(-1.01, 0.31)*	*(-0.82, 0.17)*	*(-0.68, 0.21)*	*(-1.05, 0.96)*	*(-1.41, 0.57)*	*(-0.17, 1.85)*

Table 2.10: Trading strategy with VIX /VXD futures based on interval forecasts from March 18, 2005 to September 28, 2007. The entries show the annualised Sharpe ratio, Leland's (1999) Alpha (A_p) and their respective bootstrapped 95% confidence intervals. The trading game is based on interval forecasts obtained from the economic variables model (Panel A), AR(1) model (Panel B), VAR model (Panel C), PCA model (Panel D), ARIMA(1,1,1) model (Panel E) and ARFIMA(1,d,1) model (Panel F). The Sharpe ratio for the S&P 500 and the Dow Jones Industrial Average is 0.0265 [*95% CI* = (-0.05, 0.10)] and 0.0319 [*95% CI* = (-0.04, 0.11)], respectively. One asterisk denotes rejection of the null hypothesis of a zero Sharpe ratio (A_p) at a 5% level of significance.

Panel A: Point Forecasts	
	Frequency (%) of cases where the RW is beaten
Sub-sample 1	15.87%
Sub-sample 2	6.35%
Sub-sample 3	11.11%
Sub-sample 4	19.05%
Sub-sample 5	18.25%
Sub-sample 6	7.94%
Panel B: Interval Foreacsts	
	Frequency (%) of cases where H_0 is accepted
Sub-sample 1	33.33%
Sub-sample 2	14.29%
Sub-sample 3	78.57%
Sub-sample 4	42.86%
Sub-sample 5	90.48%
Sub-sample 6	35.71%

Table 2.11: Pseudo out-of-sample statistical evaluation of point and interval forecasts. The entries show the frequency of cases where the random walk model (RW) is beaten in terms of the RMSE, MAE and MCP (Panel A) and the frequency of cases where the null hypothesis (H_0) in Christoffersen's (1998) test is accepted (Panel B), for all six sub-samples under consideration.

	VIX Shortest Series						VXD Shortest Series					
	Macro	**AR(1)**	**VAR**	**PCA**	**ARIMA**	**ARFIMA**	**Macro**	**AR(1)**	**VAR**	**PCA**	**ARIMA**	**ARFIMA**
Panel A: Sharpe Ratio												
Sub-sample 1	0.0969	0.0490	-0.0382	-0.0094	-0.0186	-0.0594	-0.0721	-0.0947	-0.0151	**0.3075***	0.1363	0.0640
	(-0.11, 0.28)	*(-0.13, 0.29)*	*(-0.22, 0.18)*	*(-0.19, 0.22)*	*(-0.25, 0.17)*	*(-0.23, 0.16)*	*(-0.42, 0.25)*	*(-0.36, 0.29)*	*(-0.33, 0.32)*	*(0.03, 0.54)*	*(-0.23, 0.39)*	*(-0.26, 0.39)*
Sub-sample 2	0.1038	-0.0064	-0.1367	-0.1537	-0.0778	-0.0040	0.0481	0.0092	-0.0217	-0.0549	0.0461	0.1273
	(-0.10, 0.30)	*(-0.18, 0.27)*	*(-0.29, 0.07)*	*(-0.31, 0.06)*	*(-0.27, 0.13)*	*(-0.18,0.27)*	*(-0.20, 0.33)*	*(-0.23, 0.31)*	*(-0.26, 0.25)*	*(-0.29, 0.23)*	*(-0.22, 0.30)*	*(-0.13, 0.39)*
Sub-sample 3	0.0006	-0.0906	0.0558	0.0009	-0.0048	-0.0400	0.0689	-0.1476	0.1826	0.1650	-0.0367	0.0120
	(-0.21, 0.19)	*(-0.26, 0.13)*	*(-0.14, 0.27)*	*(-0.19, 0.22)*	*(-0.22, 0.18)*	*(-0.21, 0.19)*	*(-0.18, 0.27)*	*(-0.34, 0.09)*	*(-0.05, 0.39)*	*(-0.06, 0.38)*	*(-0.30, 0.18)*	*(-0.25, 0.22)*
Sub-sample 4	-0.0364	0.0354	0.1100	-0.0718	0.0527	0.1392	-0.1000	0.0292	0.0555	**0.2025***	**0.2392***	**0.2017***
	(-0.20, 0.19)	*(-0.17, 0.22)*	*(-0.09, 0.28)*	*(-0.24, 0.13)*	*(-0.16, 0.23)*	*(-0.06, 0.30)*	*(-0.28, 0.10)*	*(-0.16, 0.27)*	*(-0.16, 0.24)*	*(0.01, 0.40)*	*(0.06, 0.42)*	*(0.01, 0.38)*
Sub-sample 5	0.0985	-0.0982	-0.0947	-0.1269	0.0200	-0.0308	-0.0294	-0.0343	0.1006	0.1049	0.0425	-0.0087
	(-0.10, 0.27)	*(-0.26, 0.12)*	*(-0.26, 0.12)*	*(-0.28, 0.08)*	*(-0.20, 0.21)*	*(-0.21, 0.18)*	*(-0.23, 0.23)*	*(-0.23, 0.27)*	*(-0.13, 0.33)*	*(-0.13, 0.33)*	*(-0.21, 0.25)*	*(-0.22, 0.24)*
Sub-sample 6	-0.0160	-0.0243	-0.0268	-0.0811	0.0523	-0.1394	-0.0529	-0.2165	0.0116	-0.0154	-0.0114	-0.0452
	(-0.21, 0.18)	*(-0.22, 0.17)*	*(-0.23, 0.17)*	*(-0.27, 0.12)*	*(-0.14, 0.26)*	*(-0.32, 0.06)*	*(-0.28, 0.18)*	*(-0.44, 0.01)*	*(-0.23, 0.25)*	*(-0.26, 0.22)*	*(-0.23, 0.24)*	*(-0.27, 0.19)*
Panel B: Leland's Alpha												
Sub-sample 1	0.5677	0.1824	-0.3053	-0.0798	-0.0930	-0.5193	-0.7134	-1.2976	0.1039	2.4923	1.0330	0.3009
	(-0.63, 1.84)	*(-0.94, 1.07)*	*(-1.74, 0.90)*	*(-1.50, 1.16)*	*(-1.31, 1.27)*	*(-1.81, 0.66)*	*(-3.81, 2.52)*	*(-4.63, 1.43)*	*(-3.02, 3.36)*	*(-0.13, 5.68)*	*(-1.86, 4.40)*	*(-2.65, 3.48)*
Sub-sample 2	0.6972	-0.0742	-0.9569	-1.0848	-0.5144	-0.0598	0.0640	-0.5828	-0.5723	-0.8871	0.5010	1.2490
	(-0.72, 2.00)	*(-1.51, 0.97)*	*(-2.52, 0.19)*	*(-2.47, 0.20)*	*(-2.05, 0.73)*	*(-1.53, 1.01)*	*(-2.13, 2.11)*	*(-2.68, 1.27)*	*(-2.95, 1.76)*	*(-3.01, 1.04)*	*(-1.94, 2.99)*	*(-1.24, 3.63)*
Sub-sample 3	-0.0076	-0.6225	0.3578	-0.0063	-0.0364	-0.2834	0.9181	-2.1535	2.5081	2.2707	-0.5549	0.0946
	(-1.44, 1.48)	*(-1.89, 0.42)*	*(1.08, 1.69)*	*(-1.56, 1.35)*	*(-1.20, 1.51)*	*(-1.50, 0.78)*	*(-1.97, 4.27)*	*(-5.97, 0.55)*	*(-0.27, 5.93)*	*(-0.65, 5.42)*	*(-3.90, 2.90)*	*(-2.37, 2.69)*
Sub-sample 4	-0.4713	-0.0383	0.9733	-0.8546	0.5395	1.3903	-0.7849	-0.3020	0.5527	**1.5158***	**2.1532***	**1.6150***
	(-2.77, 1.91)	*(1.84, 1.57)*	*(-1.11, 3.57)*	*(-3.20, 1.50)*	*(-1.59, 3.15)*	*(-0.78, 3.66)*	*(-2.79, 0.75)*	*(-1.69, 1.17)*	*(-1.25, 2.20)*	*(0.03, 3.48)*	*(0.42, 3.83)*	*(0.19, 3.56)*
Sub-sample 5	1.1778	-1.1201	-1.1256	-1.4937	0.2269	-0.3350	-0.4346	-0.8236	1.2379	1.4919	0.7656	-0.2518
	(-1.11, 3.97)	*(3.36, 0.55)*	*(-3.77, 0.91)*	*(-4.01, 0.49)*	*(-1.98, 2.73)*	*(-2.21, 1.52)*	*(-3.83, 2.38)*	*(-3.51, 1.24)*	*(-1.89, 4.98)*	*(-1.65, 4.94)*	*(-1.94, 3.99)*	*(-3.45, 2.72)*
Sub-sample 6	-0.0380	-0.5014	-0.2585	-0.7551	0.2863	-1.4172	-0.7151	**-2.7952***	0.1955	-0.1717	-0.2003	-0.6264
	(-1.82, 1.83)	*(-1.94, 1.00)*	*(-2.04, 1.38)*	*(-2.53, 0.86)*	*(-1.39, 1.91)*	*(-2.72, -0.43)*	*(-3.59, 2.25)*	*(-4.73, -0.71)*	*(-2.86, 3.02)*	*(-3.24, 2.85)*	*(-2.73, 2.54)*	*(-3.36, 2.09)*

Table 2.12: Pseudo out-of-sample trading strategies with the VIX and VXD shortest futures series based on point forecasts from March 18, 2005 to September 28, 2007. The entries show the annualised Sharpe ratio (Panel A), Leland's Alpha (Panel B) and their respective bootstrapped 95% confidence intervals within parenthesis for the trading strategies with the VIX and VXD shortest series and for all sub-samples under consideration. The trading strategies are based on point forecasts obtained from the economic variables model [equation (2.1)], the AR(1) model [equation (2.2)], the VAR model [equation (2.3)], the PCA model [equation (2.4)], the ARIMA(1,1,1) model [equation (2.5)] and the ARFIMA(1,*d*,1) model [equation (2.6)].

	VIX Shortest Series						VXD Shortest Series					
	Macro	AR(1)	VAR	PCA	ARIMA	ARFIMA	Macro	AR(1)	VAR	PCA	ARIMA	ARFIMA
Panel A: Sharpe Ratio												
Sub-sample 1	0.0275	0.0036	-0.0799	-0.0838	-0.0434	-0.0694	0.1820	-0.0748	-0.2910	0.0723	0.2296	0.0334
	(-0.19, 0.21)	*(-0.18, 0.23)*	*(-0.25, 0.13)*	*(-0.26, 0.12)*	*(-0.28, 0.14)*	*(-0.25, 0.14)*	*(-0.16, 0.44)*	*(-0.34, 0.33)*	*(-0.53, 0.00)*	*(-0.25, 0.42)*	*(-0.09, 0.49)*	*(-0.31, 0.34)*
Sub-sample 2	0.0405	-0.0349	-0.1409	-0.0992	-0.0780	-0.0364	0.0794	-0.0749	-0.0211	-0.0366	0.1514	0.0326
	(-0.17, 0.23)	*(-0.20, 0.22)*	*(-0.30, 0.07)*	*(-0.26, 0.12)*	*(-0.28, 0.13)*	*(-0.21, 0.22)*	*(-0.16, 0.38)*	*(-0.30, 0.20)*	*(-0.26, 0.26)*	*(-0.26, 0.26)*	*(-0.11, 0.39)*	*(-0.20, 0.34)*
Sub-sample 3	0.0205	-0.1049	0.0609	-0.0170	0.0022	-0.0277	0.0388	-0.0921	0.1469	0.1052	0.0127	0.0031
	(-0.19, 0.21)	*(-0.27, 0.11)*	*(-0.14, 0.28)*	*(-0.20, 0.20)*	*(-0.22, 0.19)*	*(-0.21, 0.19)*	*(-0.22, 0.24)*	*(-0.38, 0.13)*	*(-0.08, 0.35)*	*(-0.15, 0.31)*	*(-0.24, 0.23)*	*(-0.26, 0.22)*
Sub-sample 4	-0.0069	0.0732	0.0553	-0.0107	0.0460	0.1144	-0.0051	0.0413	0.0571	0.1475	0.1809	0.1826
	(-0.19, 0.22)	*(-0.13, 0.25)*	*(-0.15, 0.23)*	*(-0.19, 0.20)*	*(-0.18, 0.21)*	*(-0.09, 0.28)*	*(-0.23, 0.19)*	*(-0.14, 0.29)*	*(-0.16, 0.25)*	*(-0.05, 0.35)*	*(-0.01, 0.35)*	*(-0.01, 0.36)*
Sub-sample 5	0.0605	-0.1165	-0.0924	-0.0679	0.1107	-0.0550	-0.0602	-0.0343	0.0513	0.0730	0.0582	0.0168
	(-0.15, 0.24)	*(-0.27, 0.09)*	*(-0.25, 0.12)*	*(-0.23, 0.15)*	*(-0.10, 0.28)*	*(-0.23, 0.16)*	*(-0.27, 0.19)*	*(-0.23, 0.25)*	*(-0.19, 0.27)*	*(-0.16, 0.30)*	*(-0.19, 0.26)*	*(-0.20, 0.28)*
Sub-sample 6	-0.0457	-0.0863	-0.0483	-0.0050	0.0673	-0.1231	-0.0241	-0.1036	-0.0464	-0.0469	-0.0397	-0.1363
	(-0.24, 0.15)	*(-0.28, 0.11)*	*(-0.25, 0.15)*	*(-0.20, 0.20)*	*(-0.13, 0.27)*	*(-0.31, 0.07)*	*(-0.26, 0.22)*	*(-0.34, 0.13)*	*(-0.30, 0.19)*	*(-0.30, 0.18)*	*(-0.27, 0.21)*	*(-0.36, 0.10)*
Panel B: Leland's Alpha												
Sub-sample 1	0.1070	-0.0909	-0.5703	-0.5910	-0.2581	-0.5903	1.6615	-1.1128	-2.6091	0.3237	2.0426	-0.0180
	(-1.09, 1.37)	*(-1.30, 0.85)*	*(-1.99, 0.68)*	*(-2.03, 0.67)*	*(-1.47, 1.12)*	*(-1.88, 0.57)*	*(-1.23, 4.86)*	*(-4.49, 1.80)*	*(-6.22, 0.29)*	*(-2.97, 3.08)*	*(-0.94, 5.61)*	*(-3.05, 3.29)*
Sub-sample 2	0.2680	-0.2670	-0.9793	-0.7196	-0.5159	-0.2727	0.3288	-1.0634	-0.5515	-0.6386	1.6026	-0.0214
	(-1.18, 1.57)	*(-1.79, 0.86)*	*(-2.48, 0.11)*	*(-2.16, 0.65)*	*(-2.05, 0.77)*	*(-1.77, 0.83)*	*(-1.87, 2.43)*	*(-3.27, 0.92)*	*(-2.94, 1.80)*	*(-2.78, 1.40)*	*(-0.67, 4.00)*	*(-2.31, 1.95)*
Sub-sample 3	0.1359	-0.7246	0.4032	-0.1316	0.0271	-0.1999	0.4875	-1.3805	2.0159	1.4371	0.1755	-0.0326
	(-1.31, 1.66)	*(-2.05, 0.36)*	*(-1.04, 1.94)*	*(-1.73, 1.19)*	*(-1.20, 1.62)*	*(-1.42, 0.84)*	*(-2.39, 3.95)*	*(-4.13, 1.62)*	*(-0.84, 5.38)*	*(-1.35, 4.48)*	*(-3.11, 3.97)*	*(-2.62, 2.82)*
Sub-sample 4	0.0072	0.5497	0.3732	-0.0715	0.6583	1.1120	-0.0092	-0.1317	0.6031	1.2149	1.5759	**1.4932***
	(-2.23, 2.35)	*(-1.38, 2.31)*	*(-1.77, 2.97)*	*(-2.30, 2.24)*	*(-1.52, 3.09)*	*(-1.09, 3.44)*	*(-1.88, 1.66)*	*(-1.57, 1.37)*	*(-1.22, 2.22)*	*(-0.30, 3.17)*	*(-0.18, 3.26)*	*(0.03, 3.42)*
Sub-sample 5	0.7347	-1.3416	-1.1018	-0.8071	1.3086	-0.6239	-0.8616	-0.8236	0.6243	0.9445	1.0572	0.0401
	(-1.58, 3.53)	*(-3.66, 0.54)*	*(-3.73, 0.99)*	*(-3.33, 1.19)*	*(-0.79, 3.94)*	*(-2.49, 1.18)*	*(-4.32, 1.98)*	*(-3.49, 1.23)*	*(-2.52, 4.15)*	*(-2.17, 4.53)*	*(-1.61, 4.09)*	*(-3.08, 3.00)*
Sub-sample 6	-0.3254	-1.0369	-0.4726	-0.1134	0.4120	**-1.2697***	-0.3435	-1.3797	-0.5475	-0.5684	-0.5654	-1.7740
	(-2.08, 1.51)	*(-2.37, 0.59)*	*(-2.20, 1.14)*	*(-1.82, 1.51)*	*(-1.35, 2.03)*	*(-2.60, -0.23)*	*(-3.32, 2.77)*	*(-4.07, 1.44)*	*(-3.69, 2.43)*	*(-3.68, 2.46)*	*(-3.09, 2.08)*	*(-4.34, 0.78)*

Table 2.13: Pseudo out-of-sample trading strategies with the VIX and VXD shortest futures series based on interval forecasts from March 18, 2005 to September 28, 2007. The entries show the annualised Sharpe ratio (Panel A), Leland's Alpha (Panel B) and their respective bootstrapped 95% confidence intervals within parenthesis for the trading strategies with the VIX and VXD shortest series and for all sub-samples under consideration. The trading strategies are based on point forecasts obtained from the economic variables model [equation (2.1)], the AR(1) model [equation (2.2)], the VAR model [equation (2.3)], the PCA model [equation (2.4)], the ARIMA(1,1,1) model [equation (2.5)] and the ARFIMA(1,*d*,1) model [equation (2.6)].

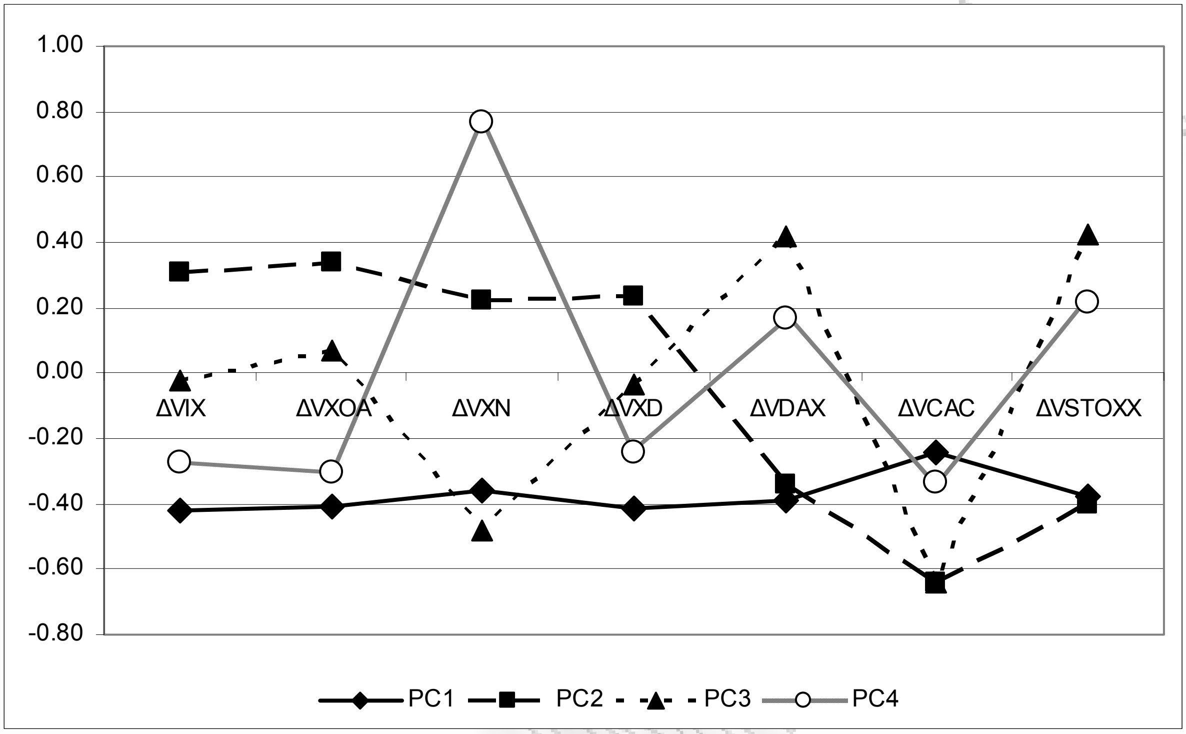

Figure 2.1: Correlation loadings of the first four PCs. Principal component analysis (PCA) has been applied on the daily changes of implied volatility indices for the period February 2, 2001 to March 17, 2005.

Chapter 3: Are VIX futures prices predictable? An empirical investigation

Abstract

This paper investigates whether volatility futures prices per se can be forecasted by studying the fast growing VIX futures market. To this end, alternative model specifications are employed. Point and interval out-of sample forecasts are constructed and evaluated under various statistical metrics. Next, the economic significance of the obtained forecasts is also assessed by performing trading strategies. Only weak evidence of statistically predictable patterns in the evolution of volatility futures prices is found. No trading strategy yields economically significant profits. Hence, the hypothesis that the VIX volatility futures market is informationally efficient cannot be rejected.

1 Introduction

Volatility derivatives have attracted much attention over the past years since they enable trading and hedging against changes in volatility. Brenner and Galai (1989, 1993) first suggested derivatives written on some measure of volatility that would serve as the underlying asset. Since then, a number of volatility derivatives have been trading in the over-the-counter market. In March 26, 2004, volatility futures on the implied volatility index VIX were introduced by the CBOE. Volatility futures on a number of other implied volatility indices have been also introduced since then. The liquidity of volatility futures markets is steadily growing, with the VIX futures market being the most liquid one.[12] This paper focuses on the VIX futures market and addresses for the first time the question whether VIX futures prices

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[12] The CBOE launched the VXD and VXN volatility futures in April 25, 2005 and July 6, 2007, respectively. The VXD and VXN are implied volatility indices that track the implied volatility of a synthetic option on the Dow Jones Industrial Average and the Nasdaq 100, respectively, with constant time to maturity (thirty days). Regarding the liquidity of volatility futures, on January 2, 2008 the open interest for VIX futures was 55,792 contracts or $1.3 billion in terms of market value; this corresponds to a 59% increase from January 3, 2007. The trading volume was 2,481 contracts or $57 million in terms of market value. On the same date, the open interest of VXD and VXN futures was $19 and $4 million, respectively.

per se can be predicted.[13] Answering the question whether volatility futures prices can be predicted is of importance to both academics and practitioners. This is because it contributes to understanding whether volatility futures markets are efficient and helps market participants to develop profitable volatility trading strategies and set successful hedging schemes.

There is already some extensive literature that has investigated whether the prices of stock index, interest rate, currency, and commodity futures can be forecasted. The significance of the results has been evaluated under either a statistical or economic (trading profits) metric. A number of studies have documented a statistically predictable pattern in futures returns. In particular, Bessembinder and Chan (1992) found that the monthly nearest maturity commodity and currency futures returns can be forecasted within sample in a statistical sense. They concluded that this predictability could be attributed to an asset pricing model with time-varying risk-premia. Similar findings were documented by Miffre (2001b) for the FTSE 100 futures and by Miffre (2001a) for commodity and financial futures.

On the other hand, the empirical evidence on the predictability in futures markets under an economic metric is mixed. For instance, Hartzmark (1987) found that in aggregate, speculators do not earn significant profits in commodity and interest rate futures markets; daily data of all contract maturities were employed. Yoo and Maddala (1991) studied commodity and currency futures and found that speculators tend to be profitable; daily data for a number of futures maturities were considered. Similar findings were reported by Taylor (1992), Kho (1996), Wang (2004) and Kearns and Manners (2004). In particular, all these studies found that economically significant profits can be obtained by employing various trading rules in currency futures markets; daily data were used by Taylor (1992), and weekly by Kho (1996), Wang (2004) and Kearns and Manners (2004). A number of futures maturities were examined by Taylor (1992) and Kearns and Manners (2004), while Kho (1996) and Wang (2004) focused on the shortest maturity series. Significant profits were also reported in Hartzmark (1991) and Miffre (2002) who examined the commodity and financial

[13] This question is distinct from the question whether futures markets are efficient in the sense that the futures price is an optimal forecast of the underlying spot price to be realized on the contract expiry date [see e.g., Nossman and Wilhelmsson (2009), for a study using VIX futures]. In our study, Jensen's (1978) definition of futures market efficiency is adopted.

futures markets; the latter study focused only on the shortest maturity contracts. Regarding the source of the identified trading profits, Taylor (1992) and Kearns and Manners (2004) attributed them to the inefficiency of the currency futures market. On the other hand, Yoo and Maddala (1991), Kho (1996), Wang (2004) and Miffre (2002) found that the reported profits were not abnormal and Hartzmark (1991) found that profitability is determined by luck rather than superior forecast ability; hence, the considered markets were efficient á la Jensen (1978).

In contrast to the number of papers devoted to the topic of predictability in the previously mentioned futures markets, the research on whether there exist predictable patterns in the evolution of volatility futures prices is still at its infancy. The literature on volatility futures has primarily focused on developing pricing models [see e.g., Grünbichler and Longstaff (1996), Zhang and Zhu (2006), Dotsis et al. (2007), Zhang et al. (2010), and Lin (2007)] and assessing their hedging performance [see e.g., Jiang and Oomen (2001)]. On the other hand, to the best of our knowledge, the only related study that has explored the issue of predictability of volatility futures markets is the one presented in Chapter 2 of this thesis. However, this has been done indirectly and only under a financial measure. In Chapter 2 we developed trading strategies with VIX and VXD volatility futures based on point and interval forecasts that were formed for the corresponding *underlying* implied volatility indices. We found that the obtained Sharpe ratios were not statistically different from zero and hence the volatility futures markets are efficient.

This study extends the literature on whether the evolution of volatility futures prices can be forecasted. In contrast to Chapter 2, in this Chapter we investigate the predictability of the VIX volatility futures prices per se without exploring the existence of predictable patterns in the underlying implied volatility index. This is because predictability in the underlying implied volatility index market does not necessarily imply that volatility futures prices can be predicted since there may be other factors/information flows that affect volatility futures markets, as well. This is analogous to the interest rate derivatives literature where it is well documented that models that describe the dynamics of the underlying interest rate quite well, cannot account for the properties of the prices of the corresponding interest rate derivative ("unspanned stochastic volatility problem", see e.g., Jarrow et al. (2007) and the references therein). In our case, the relationship between changes in the prices of VIX futures and its underlying is not known a priori from a theoretical point of view; there is no cost-of-carry relationship in the case of VIX futures since the underlying index is not a tradable asset. In addition, volatility futures prices may not always be moving to the same direction with the underlying implied volatility index due to market microstructure effects [see a similar discussion and findings in Bakshi et al. (2000b) who conducted an analysis for call options using intra-day data].

To address our research question, both point and bootstrapped interval out-of-sample forecasts are considered. This is because interval forecasts have been found to be useful for volatility trading purposes; Poon and Pope (2000) found that profitable volatility spread trades can be developed in the S&P 100 and S&P 500 index option markets by constructing certain intervals. We test the statistical significance of the obtained forecasts by a number of tests and criteria. In addition, their economic significance is investigated by means of trading strategies. This is the ultimate test to conclude whether the recently inaugurated volatility futures market is efficient. To check the robustness of our results, the analysis is performed across various maturity futures series and by employing a number of alternative model specifications. The latter is necessary since the question of predictability is tested inevitably jointly with the assumed forecasting model.

The remainder of this paper is structured as follows. Section 2 describes the data set. Section 3 presents the forecasting models to be used. Section 4 discusses the results concerning the in-sample performance of the models under consideration. Next, the out-of-sample predictive performance of the various models is evaluated in statistical and economic terms in Sections 5 and 6, respectively. The last section concludes.

2 The data set

Daily settlement prices of CBOE VIX volatility futures and a set of economic variables are used. The sample period under consideration is from March 26, 2004 to March 13, 2008. The subset from March 18, 2005 to March 13, 2008 is used for the out-of-sample evaluation.

VIX futures were listed in March 26, 2004 by the CBOE. These are exchange-traded futures contracts on volatility and may be used to trade and hedge volatility. The underlying asset of these contracts is VIX [see Appendix A, B and C for the construction and interpretation of VIX]. The contract size is $1,000 times the VIX.[14] On any day, the CBOE Futures Exchange (CFE) may list for trading up to six near-term serial months and five months on the February quarterly cycle for the VIX futures contract. The VIX futures contracts are cash settled. The final settlement date is the Wednesday that is thirty days prior to the third Friday of the calendar month immediately following the month in which the contract expires.

The VIX futures prices are obtained from the CBOE website. By ranking the data based on their time to expiration, three time series of futures prices are constructed; namely, the shortest, second shortest, and third shortest maturity series. To minimize the impact of noisy data, we roll over to the next maturity contract five trading days before the contract expires [see also Dotsis et al., 2007]. Similarly, settlement prices corresponding to a trading volume less than five contracts are excluded.

The data set of economic variables consists of the return on the S&P 500 stock index, the one-month Libor interbank rate, the slope of the yield curve, calculated as the difference between the prices of the ten-year U.S. government bond and the one-month interbank rate, and the basis, calculated as the difference between the VIX index and the VIX futures price for a given maturity *T*. These data are obtained from Datastream.

Figure 3.1 shows the evolution of the three maturity VIX futures series and the VIX index over the period from March 26, 2004 to March 13, 2008. Until March 2007, the term structure of futures prices appears to be upward sloping, with prices being higher for longer maturities [see also Brenner et al., 2008]. Table 3.1 shows the summary statistics for the three series of futures' prices and the economic variables in levels and first differences (Panel A and B, respectively). All variables measured in levels are positively (first order) autocorrelated; this is not the case when they are measured in first differences. The Augmented Dickey Fuller (ADF) test indicates that most of the VIX futures price series, the S&P 500 and the one-month Libor rate are non-stationary in the levels, but stationary in the

[14] On March 26, 2007, the VIX futures were rescaled in two ways. First, VIX futures were based directly on the underlying VIX volatility index instead on the "Increased-Value index" (VBI=10*VIX). Second, the multiplier was increased from $100 to $1,000. As a result, the traded futures prices were reduced by a factor of 10, but the $ value of each contract did not change. We adjusted the VIX futures series accordingly.

first differences. Furthermore, the slope of the yield curve and the basis for most of the futures series are stationary in the levels. The average volume decreases for longer maturities.

3 The forecasting models

3.1 Economic variables model

We use a set of lagged economic variables to forecast the evolution of futures prices. This model specification tests the semi-strong form efficiency of the volatility futures market [see also Bessembinder and Chan (1992), Miffre (2001a, 2001b, 2002), Kearns and Manners (2004) for applications of similar predictive specifications to futures markets]. Based on the BIC criterion, the following regression is estimated:

$$\Delta F_{t,T} = c + a_1 \Delta F_{t-1,T} + a_2 R_{t-1} + a_3 i_{t-1} + a_4 ys_{t-1} + a_5 basis_{t-1,T} + \varepsilon_{t,T} \qquad (3.1)$$

where $\Delta F_{t,T}$ denotes the daily changes in the futures price between time *t-1* and *t* for a given maturity *T* (*T*=1, 2, 3), *c* a constant, R_t the log-return on the S&P 500 stock index between time *t-1* and *t*, i_t the one-month Libor rate in log-differences, ys_t the slope of the yield curve, and $basis_{t,T}$ is the difference between the VIX index and the VIX futures price for a given maturity *T*. The employed variables have been shown to have forecast power in equity markets [see e.g., Welch and Goyal (2008)] and hence they may also have predictive power in futures markets. In addition, the slope of the term structure of interest rate has been shown to be able to forecast a forthcoming recession [see e.g., Estrella and Hardouvelis (1991)] and hence an increase in volatility [Schwert (1989)] and volatility futures prices. Figure 3.2 shows the evolution of the slope of the yield curve over the period March 26, 2004 to March 13, 2008. Furthermore, the basis may have the ability to forecast the futures risk premium, since it can be decomposed in two terms: the risk premium of the futures contract and the expected change in the underlying asset price [Fama and French (1987)]. Finally, notice that changes in the underlying implied volatility index have not been used as an additional predictive variable so as to avoid multi-collinearity issues; VIX is highly correlated with the VIX futures prices.

3.2 Univariate autoregressive, ARMA and VAR Models

Univariate autoregressive, ARMA and VAR models are employed to investigate the extent to which past volatility futures prices can be exploited for predictive purposes and to examine whether there are spillovers between the three futures series. These model specifications set up tests of weak form market efficiency. The employed number of lags is chosen on the basis of the BIC criterion and to avoid over-fitting the data (the maximum number of lags considered was four). The following AR(2) model is estimated:

$$\Delta F_{t,T} = c + \varphi_1 \Delta F_{t-1,T} + \varphi_2 \Delta F_{t-2,T} + \varepsilon_{t,T} \tag{3.2}$$

We estimate also an ARMA(1,1) model:

$$\Delta F_{t,T} = c + \varphi_1 \Delta F_{t-1,T} + \theta_1 \varepsilon_{t-1,T} + \varepsilon_{t,T} \tag{3.3}$$

Furthermore, the following VAR(1) model is estimated:

$$\Delta F_t = C + \Phi_1 \Delta F_{t-1} + \varepsilon_t \tag{3.4}$$

where ΔF_t is the (3×1) vector of changes in the three futures prices series that are assumed to be jointly determined, C is a (3×1) vector of constants, Φ_1 is a (3×3) matrix of coefficients and ε_t is a (3×1) vector of residuals.

3.3 Combination forecasts

Apart from model based forecasts, we also consider combination forecasts. Combination forecasts aggregate the information used by the individual forecasting models. They have been found to be more accurate than individual forecasts [see e.g., Bates and Granger (1969) and Clemen (1989) for a review].

Two alternative linear combination forecasts are considered. First, an equally weighted combination forecast is employed:

$$\hat{F}^{EW}_{t|t-1,T} = \frac{1}{4}\sum_{i=1}^{4} \hat{F}^{i}_{t|t-1,T} \tag{3.5}$$

where $\hat{F}^{i}_{t|t-1,T}$ is the forecasted futures price constructed at time *t*-1 for *t* for a given maturity *T* by using the *i*-th model specification [*i* = 1 (economic variables model), 2 (AR(2) model), 3

(ARMA(1,1) model), 4 (VAR model)], and $\hat{F}^{EW}_{t|t-1,T}$ denotes the equally weighted combination forecast of the futures price constructed at time t-1 for t for a given maturity T. This is a simple average of all model based forecasts; there is evidence that simple combinations frequently outperform more sophisticated ones [see e.g., Clemen (1989)].

Second, a non-equally weighted average of the individual forecasts is used; the weights are chosen so as to minimize the mean squared forecast error [see Granger and Ramanathan (1984)]. To fix ideas, standing at time t, the weights are obtained by estimating the following OLS regression recursively:

$$\Delta F_{t,T} = c + \sum_{i=1}^{4} a_i \Delta \hat{F}^{i}_{t|t-1,T} + \varepsilon_{t,T} \tag{3.6}$$

where $\Delta F_{t,T}$ is the realized futures price change between time t-1 and t for a given maturity T, c is a constant, $\Delta \hat{F}^{i}_{t|t-1,T} = \hat{F}^{i}_{t|t-1,T} - F_{t-1,T}$ is the forecasted futures price change between time t-1 and t for a given maturity T and $\varepsilon_{t,T}$ is the error term. Then:

$$\hat{F}^{W}_{t+1|t,T} = F_{t,T} + c + \sum_{i=1}^{4} a_i \Delta \hat{F}^{i}_{t+1|t,T} \tag{3.7}$$

where $\hat{F}^{W}_{t+1|t,T}$ denotes the weighted combination forecast of the futures price constructed at t for t+1 for a given maturity T.

To start constructing the weighted combination forecasts recursively, one needs an "initial" time series of individual forecasts to estimate regression (3.6). To this end, the in-sample data (from March 26, 2004 to March 17, 2005) are divided into an in-sample period (from March 26, 2004 to September 24, 2004) and a "pseudo" out-of-sample period (from September 27, 2004 to March 17, 2005). First, the in-sample data are used to estimate the model specifications described in Section 3.1-3.2 [equations (3.1), (3.2), (3.3), (3.4)]. Then, forecasts are formed recursively over the "pseudo" out-of-sample period by adding each observation of the "pseudo" out-of-sample data set to the in-sample data set as it becomes available. Finally, the individual forecasts over the "pseudo" out-of-sample period are used to estimate regression (3.6). Then, the first out-of-sample weighted combination forecast (corresponding to March 18, 2005) is constructed as described by equation (3.7). To form the remaining out-of-sample combination forecasts, equation (3.6) is estimated recursively by adding each individual forecast to the sample as it becomes available and equation (3.7) is re-applied.

4. In-sample evidence

Tables 3.2 and 3.3 show the in–sample performance of the economic variables and the AR(1)/ARMA(1,1)/VAR, respectively. The estimated coefficients, the *t*-statistics within parentheses, the unadjusted R^2 and the adjusted R^2 are reported for each one of the implied volatility indices, respectively. One and two asterisks indicate that the estimated parameters are statistically significant at 1% and 5% level, respectively.

In the case of the economic variables model [Table 3.2], we can see that the adjusted R^2 takes the largest value for the third shortest series (0.9%). This is similar to the values of adjusted R^2 documented by the previous related literature in various futures markets [see Bessembinder and Chan (1992), Miffre, 2001a, 2001b, 2002]. In the case of AR(2) and VAR models [Table 3.3, Panel A and Panel B, respectively], we can see that the largest values of the adjusted R^2 are obtained for the second shortest series (1.9% and 3.1%, respectively). Finally, the application of the ARMA model [Table 3.3, Panel C], reveals that there is a predictable pattern in the case of the shortest futures series (adjusted R^2 equals 5.5%).

To sum up, the in-sample goodness-of-fit depends on the model specification and the maturity of the futures series under consideration. Next, the out-of-sample performance is assessed so as to provide a firm answer to the question whether volatility futures prices can be forecasted.

5 Out-of-sample evidence: Statistical significance

Point and bootstrapped interval forecasts are used to assess the out-of-sample performance of the models described in Section 3. The out-of-sample period is from March 18, 2005 to March 13, 2008. To form the point forecasts, the models are initially estimated over the in-sample period (from March 26, 2004 to March 17, 2005) and the first out-of-sample point forecast is obtained (corresponding to March 18, 2005). To construct the remaining out-of-sample point forecasts, the models are re-estimated recursively by adding each observation to the in-sample data set as it becomes available. The bootstrapped interval forecasts are constructed by applying the methodology suggested by Pascual et al. (2001) so as take into account the non-normality of the residuals of the various models and the parameter uncertainty [see Appendix G for a description of the construction algorithm of the bootstrapped interval forecasts]. To this end, on each time step (i.e., day) 1,000 bootstrap samples are formed.

5.1 Point forecasts: Statistical testing

To assess the statistical significance of the obtained out-of-sample point forecasts, three alternative metrics are employed. The first metric is the root mean squared prediction error (RMSE) calculated as the square root of the average squared deviations of the actual volatility futures prices from the model based forecast, averaged over the number of observations. The second metric is the mean absolute prediction error (MAE) calculated as the average of the absolute differences between the actual volatility futures price and the model based forecast, averaged over the number of observations. The third metric is the mean correct prediction (MCP) of the direction of volatility futures price changes calculated as the average frequency (percentage of observations) for which the predicted by the model change in the volatility futures price has the same sign as the realized change. The forecasts are compared to those obtained from the random walk that is used as the benchmark model. To this end, we perform pairwise comparisons based on the modified Diebold and Mariano (1995) test [MDM, see Harvey et al. (1997)] and a ratio test for the RMSE/MAE and MCP metrics, respectively. The null hypothesis is that the model under consideration and the random walk perform equally well. Moreover, we use White's (2000) test (also termed reality check) to compare *jointly* all forecasts to the benchmark model under the RMSE and MAE metrics.[15] In this case, the null hypothesis is that no model outperforms the random walk.

To fix ideas, the two tests are described as follows. Let $\left\{\hat{F}^i_{t|t-1,T}\right\}_{t=1}^{n}$ and

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[15] Note that the MCP cannot be calculated for the random walk model. However, we proxy the random walk with the naïve rule that "the predicted change in the futures prices has a 50% chance to be positive and a 50% to be negative". This is to say that the random walk case corresponds to an MCP equal to 50%. Similarly, White's (2000) test can not applied to the MCP metric. This is because the corresponding loss function cannot be defined for the benchmark model.

$\left\{\hat{F}^{RW}_{t|t-1,T}\right\}^{n}_{t=1}$ denote the sequence of forecasted futures price from t=1 to n based on the i-th model [i = 1 (economic variables model), 2 (AR(2) model), 3 (VAR model), 4 (ARMA(1,1)model), 5 (equally weighted combination forecast), 6 (weighted combination forecast)] and the random walk, respectively. Define a loss function $g\left(e^{i}_{t,T}\right)$ and $g\left(e^{RW}_{t,T}\right)$ and the loss differential $d^{i}_{t,T} = g\left(e^{i}_{t,T}\right) - g\left(e^{RW}_{t,T}\right)$, with $\left\{e^{i}_{t,T}\right\}^{n}_{t=1}$ and $\left\{e^{RW}_{t,T}\right\}^{n}_{t=1}$ being the respective forecast errors for the ith model specification and the T-maturity futures series.

In the case of the MDM test, the null hypothesis is $H_0 : E\left(d^{i}_{t,T}\right) = 0$. We test this against two alternative hypotheses. The first alternative hypothesis is that the random walk outperforms the respective model, i.e. $H_1 : E\left(d^{i}_{t,T}\right) > 0$. The second alternative hypothesis is that the model under consideration outperforms the random walk, i.e. $H_2 : E\left(d^{i}_{t,T}\right) < 0$.[16] In the case of one-step ahead forecasts, the MDM test statistic MDM^{i}_{T} for the ith model specification and the T-maturity futures series is given by:

$$MDM^{i}_{T} = \frac{\overline{d}^{i}_{T}}{\sqrt{\text{var}(\overline{d}^{i}_{T})}} \tag{3.8}$$

with $\overline{d}^{i}_{T} = \frac{\sum_{t=1}^{n} d^{i}_{t,T}}{n}$ and $\text{var}(\overline{d}^{i}_{T})$ a Newey and West (1987) estimator of the variance of $\overline{d}^{i}_{T}$ where Barlett's kernel was employed and the required lag selection parameter was set equal to $\left[4\left(n/100\right)^{2/9}\right]$. Following Harvey et al. (1997), we make accept/reject decisions by comparing the calculated test statistic to the critical values from the Student's t distribution with (n-1) degrees of freedom.

The idea of White's (2000) test is as follows [see also Sullivan et al. (1999)]. At any point in time t the performance measure $\hat{f}^{i}_{t,T}$ is defined for the i-th model and for a given maturity T:

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[16] In the case of the MCP, the H_1 and H_2 hypotheses are stated as H_1: MCP < 50% and H_2: MCP > 50% [see Appendix D for the testing procedure in this case].

$$\hat{f}^i_{t,T} = -d^i_{t,T} \tag{3.9}$$

So, the null hypothesis is that no model outperforms the random walk model, i.e. $H_0 : \max_{i=1,\dots,k} E\left(f^i_T\right) \le 0$. The test statistic for the observed sample is:

$$\bar{V} = \max_{i=1,\dots,k} \left\{ \sqrt{n}\left(\bar{f}^i_T\right) \right\} \tag{3.10}$$

where $\bar{f}^i_T = \sum_{t=1}^{n} \hat{f}^i_{t,T} \Big/ n$. White (2000) suggests that the null hypothesis can be evaluated by applying the stationary bootstrap of Politis and Romano (1994) to the observed values of $\hat{f}^i_{t,T}$ [see Appendix F for a description of the stationary bootstrap algorithm].[17] In particular, B bootstrapped samples of $\hat{f}^i_{t,T}$ are generated. For each bootstrap sample, the following statistic is calculated:

$$\bar{V}_j = \max_{i=1,\dots,k} \left\{ \sqrt{n}\left(\bar{f}^{i*}_{T,j} - \bar{f}_{i,T}\right) \right\} \tag{3.11}$$

where j = 1, 2, … B and $\bar{f}^{i*}_{T,j}$ are the bootstrapped values of $\bar{f}^i_T$ We choose B = 1,000. White's (2000) reality check p-value is then obtained by comparing $\bar{V}$ and the obtained $\bar{V}_j$ for j = 1, 2, … B.

5.2 Interval forecasts: Statistical testing

Christoffersen's (1998) likelihood ratio test of unconditional coverage is used to evaluate the constructed interval forecasts. The test can be applied for any assumed underlying stochastic process, since is not model dependent Christoffersen (1998). The idea of the test is as follows. A sample path $\left\{F_{t,T}\right\}_{t=1}^{n}$, of futures prices for a given maturity is observed and a series of interval forecasts $\left\{(L^i_{t/t-1,T}\left(1-a\right),\ U^i_{t/t-1,T}\left(1-a\right)\right\}_{t=1}^{T}$ is constructed. $L^i_{t/t-1,T}\left(1-a\right)$ and

[17] The stationary bootstrap involves re-sampling *blocks* of random size from the original time series to form a pseudo time series (or a bootstrapped sample). The block size follows a geometric distribution with mean block length $1/q$. Following Sullivan et al. (1999), we choose q = 0.1 that corresponds to a mean block size of 10. This is a reasonable block size given the low autocorrelation in $\hat{f}_{i,t,T}$ (results are not reported). As a robustness check, we have also performed White's (2000) test for alternative mean block size of 2, 20, and 30. We found that the results are not sensitive to the choice of the average block size (results not reported).

$U^i_{t/t-1,T}(1-a)$ denote the lower and upper bound of an (1-*a*)%-interval forecast for time *t* constructed at *t*-1 for a given maturity contract based on the *i*-th model, respectively. We test whether the (1-*a*)%-interval forecast is "efficient", i.e. whether the percentage of times that the realized future price at time *t* falls outside the interval forecast for time *t* constructed at time *t*-1 is *a*% for a given maturity. To this end, an indicator function $I^i_{t,T}$ is defined:

$$I^i_{t,T} = \begin{cases} 0, & \text{if } \mathrm{F_{t,T}} \in \left[L^i_{t/t-1,T}(1-a), U^i_{t/t-1,T}(1-a)\right] \\ 1, & \text{if } \mathrm{F_{t,T}} \notin \left[L^i_{t/t-1,T}(1-a), U^i_{t/t-1,T}(1-a)\right] \end{cases} \tag{3.12}$$

Thus, the null hypothesis of an efficient (1-*a*)% interval forecast H_0: $E(I^i_{t,T}) = \alpha$ is tested against the alternative H_1: $E(I^i_{t,T}) \neq \alpha$. Under the null hypothesis, Christoffersen's (1998) test statistic is given by a likelihood ratio test [see Christoffersen, 1998]. However, the power of this test may be sensitive to the sample size. Hence, MC simulated *p*-values are generated to assess the statistical significance of our results [see Appendix E for a description of the MC simulation]. We construct 99% and 95% interval forecasts to assess the robustness of the obtained results across different levels of significance.

5.3 Point and interval forecasts: Results

In the case of point forecasts, Table 3.4 shows the RMSE, MAE and MCP obtained for point forecasts based on the random walk model (Panel A), the economic variables model (Panel B), the AR(2) model (Panel C), the VAR model (Panel D) and the ARMA(1,1) model (Panel E). Results for the equally weighted and the weighted combination of point forecasts (Panel F and G, respectively) are also reported. One and two asterisks (crosses) denote rejection of the null hypothesis in favor of the alternative H_1 (H_2) at significance levels 1% and 5%, respectively, by the MDM and ratio tests. We can see that there are 6 (out of 54 possible combinations in total) combinations of futures series and predictability metrics in which the random walk beats one of the models (i.e., 11% of the cases). On the other hand, in 4 out of 54 cases (i.e., 7%) the model under consideration outperforms the random walk. All of these occur under the MCP measure and for the shortest series. Note that under the assumption of independence of accept/reject decisions, one would expect the models to beat the random walk only in roughly 3 out of 54 cases (i.e., 5% of the cases) at a 5% significance level. Thus, there is weak evidence of a statistically predictable pattern in the evolution of the shortest futures series.

In the case of White's (2000) test, the reality check p-value for the RMSE (MAE) is 0.998 (0.530), 0.999 (0.789) and 0.815 (0.377) for the shortest, second shortest and third shortest series, respectively. Thus, we accept the null hypothesis in all cases. This implies that even the best performing model specification under the RMSE (MAE) metric does not outperform the random walk.

Regarding interval forecasts, Table 3.5 shows the percentage of observations that fall outside the constructed 99% and 95%-interval forecasts, and Christoffersen's (1998) test statistic value obtained by the economic variables model, the AR(2) model, the VAR model, the ARMA(1,1) model, the equally weighted combination interval forecasts and the weighted combination interval forecasts (Panels A, B, C, D, E and F, respectively); results are reported for each one of the three futures series. One and two asterisks denote rejection of the null hypothesis at 1% and 5% significance levels, respectively. We can see that the null hypothesis of efficient interval forecasts is rejected in all instances. This holds for both the 99% and 95% interval forecasts.

6 Out-of-sample evidence: Economic significance

The previously reported results on point forecasts suggest that there is a weak evidence of a statistically predictable pattern in the evolution of the shortest futures series based on the MDM test. Moreover, none of the bootstrapped 99% and 95%-interval forecasts were found to be efficient. To provide a definite answer on the issue of predictability in volatility futures markets, the economic significance of the obtained forecasts is assessed by performing trading strategies based on point and interval forecasts. The trading strategies are performed despite the fact that there is no evidence of a statistically predictable pattern. This is because the statistical evidence does not always corroborate a financial criterion [see e.g., Ferson et al., 2003]. The trading strategies involve a single volatility futures contract. Transaction costs have been taken into account; the standard transaction fee in the VIX futures market is $0.50 per transaction; this represents 0.003% of the contract value on average for each futures series under consideration.

6.1 Testing for economic significance: Measures of performance

The profitability of the trading strategies is evaluated in terms of the Sharpe Ratio (SR), Leland's (1999) alpha (A_p). The statistical significance of the two performance measures is assessed by bootstrapping their 95% confidence intervals. To this end, the stationary bootstrap of Politis and Romano (1994) has been employed [see Appendix F for a description of the stationary bootstrap algorithm].[18] The continuously compounded one month Libor rate is used as the risk free rate to calculate both measures of performance.

Leland's (1999) alpha is employed in order to account for the presence of non-normality in the distribution of the trading strategy's returns. It is defined as:

$$A_p = E\left(r_p\right) - B_p\left[E\left(r_{mkt}\right) - r_f\right] - r_f \tag{3.13}$$

where r_p is the return on the trading strategy, r_f is the risk-free rate of interest, r_{mkt} is the return on the market portfolio, $B_p = \dfrac{\operatorname{cov}\left(r_p, -\left(1+r_{mkt}\right)^{-\gamma}\right)}{\operatorname{cov}\left(r_{mkt}, -\left(1+r_{mkt}\right)^{-\gamma}\right)}$ is a measure of risk similar to the CAPM's beta and $\gamma = \dfrac{\ln\left[E\left(1+r_{mkt}\right)\right] - \ln\left(1+r_f\right)}{\operatorname{var}\left[\ln\left(1+r_{mkt}\right)\right]}$ is a measure of risk aversion.

A two step procedure is employed to calculate Leland's (1999) alpha. First, γ and B_{str} are computed for each time step. We use the one month continuously compounded Libor rate and the return on the S&P 500 as proxies for the r_f and r_{mkt}, respectively. Second, the following regression is estimated:

[18] We use the stationary bootstrap method to get the confidence intervals for the SR and the alpha estimates so as to take into account the non-normality of the returns of the trading strategies; these exhibit excess kurtosis and skewness that range from 6 to 13 and from –1 to 2 respectively, across the three futures maturities. The non-normality of volatility futures returns is consistent with previous findings in the related literature for other futures markets [see e.g., Taylor (1985), and the references therein). Given the untabulated low autocorrelation in excess returns, the average block size was chosen to be 10 (i.e. q = 0.1). As a robustness check, we have also constructed bootstrapped confidence intervals for alternative mean block size of 2, 20, and 30. We found that the results on SR and alpha are robust to the choice of q.

$$r_{p,t}^{i} - B_{p,t}^{i}\left[r_{mkt,t} - r_{f,t}\right] - r_{f,t} = A_{p}^{i} + \varepsilon_{t} \tag{3.14}$$

where $r_{p,t}^{i}$ and A_{p}^{i} are the return on the trading strategy and Leland's (1999) alpha, respectively, that are based on the forecasts from the *i*-th model [i = 1 (economic variables model), 2 (AR(2) model), 3 (VAR model), 4 (ARMA(1,1) model), 5 (equally weighted combination forecast), 6 (weighted combination forecast)]. If $A_{p}^{i} > 0$ then we conclude that the trading strategy offers an expected return in excess of its equilibrium risk adjusted level.

6.2 Trading strategy and results based on point forecasts

The economic significance of the constructed point forecasts is evaluated in terms of the following trading rule:

If $F_{t-1,T}$ < (>) $\hat{F}_{t|t-1,T}^{i}$, then go long (short).

If $F_{t-1,T} = \hat{F}_{t|t-1,T}^{i}$, then do nothing.

The rational of this trading rule is as follows: If the current futures price is higher (lower) than the forecasted futures price, then the price is anticipated to decrease (increase) and the investor goes short. If the current futures price is equal to the forecasted futures price, then the investor takes no action and maintains his/her position.

Table 3.6 shows the annualised SR, A_p, and their respective bootstrapped 95% confidence intervals (95% CI) for the three VIX futures series. Results are reported for trading strategy based on point forecasts derived by the economic variables model (Panel A), the AR(2) model (Panel B), the VAR model (Panel C), the ARMA(1,1) model (Panel D), and the equally weighted (Panel E) and the weighted (Panel F) combination point forecasts. We can see that the SR and A_{p} are insignificant in all but one cases. This implies that almost all trading strategies based on point forecasts do not yield economically significant profits. The results are similar to those obtained for a naïve buy and hold strategy in VIX futures that yields a SR equal to 0.0178 [95% CI = (-0.07, 0.08)] for the shortest series, 0.0421 [95% CI = (-0.02, 0.10)] for the second shortest series, and 0.0532 [95% CI = -0.01, 0.12)] for the third shortest series.

6.3 Trading strategy and results based on interval forecasts

The economic significance of the bootstrapped interval forecasts is evaluated in terms of the following trading rule:

If $F_{t-1,T} < (>) \dfrac{U^i_{t|t-1,T}(1-\alpha)+L^i_{t|t-1,T}(1-\alpha)}{2}$, then go long (short).

If $F_{t-1,T} = \dfrac{U^i_{t|t-1,T}(1-\alpha)+L^i_{t|t-1,T}(1-\alpha)}{2}$, then do nothing.

The rationale behind this trading rule is as follows: If the futures price is closer to the lower (upper) bound of next day's interval forecasts, then we anticipate the index price to increase (decrease) and as a result the investor should go long (short).

Table 3.7 shows the annualised SR, A_p, and their respective bootstrapped 95% confidence intervals (95% CI) for the three VIX futures series. Results are reported for the trading strategy based on 99% and 95%-bootstrapped interval forecasts derived by the economic variables model (Panel A), the AR(2) model (Panel B), the VAR model (Panel C), the ARMA model (Panel D), and the weighted (Panel E) and equally weighted (Panel F) combination interval forecasts. We can see that the results are similar for the strategies based on the 99% and 95%-bootstrapped interval forecasts. In particular, the SR and A_p are insignificant in all cases. This means that overall, the trading strategies based on bootstrapped interval forecasts do not yield significant profits, just as was the case with the trading strategies based on point forecasts. The results are similar to those obtained for a naïve buy and hold strategy in VIX volatility futures. In particular, the SR equals 0.0178 [95% CI = (-0.07, 0.08)] for the shortest series, 0.0421 [95% CI = (-0.02, 0.10)] for the second shortest series, and 0.0532 [95% CI = -0.01, 0.12)] for the third shortest series.

7 Conclusions

This paper has investigated for the first time whether the volatility futures prices per se can be forecasted. To this end, the most liquid volatility futures market (futures on VIX) has been considered. A number of alternative model specifications have been employed: the economic variables model, the AR(2) model, the VAR model and the ARMA(1,1) model. Equally weighted and weighted combination forecasts have also been considered. Point and bootstrapped interval forecasts have been constructed and their statistical and economic significance has been evaluated. The latter is assessed by means of trading strategies using the VIX futures. This has implications for the efficiency of the VIX volatility futures market.

Regarding the statistical significance of the obtained forecasts, in the case of point forecasts, we found weak evidence of a statistically predictable pattern in the evolution of the shortest futures series. In the case of the interval forecasts, no model specification had predictive power. Regarding the economic significance of the obtained forecasts, the constructed forecasts did not yield economically significant profits.

Overall, our results imply that one cannot reject the hypothesis that the VIX volatility futures market is informationally efficient. These findings are consistent the results presented in Chapter 2, where the efficiency of the VIX futures market had been studied indirectly. On the other hand, our results are in contrast to those found about the efficiency of other futures markets (stock, currency, interest rate and commodities) where predictability in either statistical or economic terms has been documented. The fact that the VIX futures market is found to be efficient does not invalidate the trading of VIX futures though. This is because VIX futures can also be used for hedging against changes in volatility. After all, this was the main motivation for their introduction [see Brenner and Galai (1989, 1993)].

Future research should investigate the issue of predictability in volatility futures markets at longer horizons. It has been well documented that the predictability in asset returns increases as the horizon increases [see e.g., Poterba and Summers (1988)]. However, a longer horizon study is beyond the scope of this paper due to data limitations, as the VIX market operates only since 2004. Intra-day data should also be used to test whether any predictable patterns may be detected within the day; this will be particularly useful for day-traders. Finally, it may be worth considering more complex model specifications given that the answer on the predictability question always depends on the assumed specification of the predictive regression.

Panel A: Summary statistics of VIX futures and economic variables (levels): Mar 26, 2004 to Mar 17, 2005									
	Shortest	**2nd Shortest**	**3rd Shortest**	**S&P 500**	**1M int. rate**	**Slope of yield curve**	**Basis for shortest**	**Basis for 2nd shortest**	**Basis for 3rd shortest**
#Observations	241	235	195	255	250	250	241	235	195
Mean	158.10	169.50	178.56	1143.97	1.83	2.48	-11.99	-24.05	-33.43
Std. Deviation	22.44	24.12	24.35	41.20	0.56	0.70	11.48	11.87	11.95
Skewness	0.06	-0.08	-0.22	0.25	0.15	0.26	-0.80	-0.38	0.19
Kurtosis	2.01	1.88	1.85	1.81	1.66	1.67	3.47	2.75	2.17
Jarque-Bera	**10.05***	**12.58***	**12.36***	**17.58***	**19.75***	**21.38***	**27.66***	**6.17****	**6.84****
ρ_1	**0.926***	**0.922***	**0.802***	**0.979***	**0.968***	**0.975***	**0.856***	**0.825***	**0.729***
ADF	**-3.76****	-2.96	-1.66	-2.24	-2.71	**-3.67****	**-4.19***	**-4.70***	-1.21
Mean Volume	186.17	135.03	104.16						
(min, max)	*(5 - 1,218)*	*(5 - 865)*	*(5 - 974)*						

Panel B: Summary statistics of VIX futures and economic variables (daily differences): Mar 26, 2004 to Mar 17, 2005					
	Shortest	**2nd Shortest**	**3rd Shortest**	**S&P 500**	**1M int. rate**
Mean	-0.2689	-0.2498	-0.4430	0.0003	0.0038
Std. Deviation	5.04	4.19	3.30	0.01	0.01
Skewness	1.86	0.65	0.54	-0.13	1.24
Kurtosis	11.62	8.45	5.12	2.95	7.34
Jarque-Bera	**838.58***	**286.46***	**37.41***	0.78	**254.16***
ρ_1	-0.004	0.082	0.042	0.039	**0.247***
ADF	**-14.93***	**-13.65***	**-10.85***	**-15.36***	**-5.80***

Table 3.1: Summary statistics. Entries report the summary statistics for each VIX futures series and the economic variables. The economic variables under consideration are the S&P 500 stock index, the one-month Libor interbank interest rate, the slope of the yield curve (calculated as the difference between the prices of a ten-year U.S. government bond and the one-month interbank rate), and the basis for each of the VIX futures series. The first order autocorrelation ρ_1, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. One and two asterisk denotes rejection of the null hypothesis at the 1% and 5% level, respectively. The null hypothesis for the Jarque-Bera and the ADF tests is that the series is normally distributed and has a unit root, respectively.

	Dependent variable **Shortest**	Dependent variable **2nd Shortest**	Dependent variable **3rd Shortest**
	Coeff. *(t-stat)*	Coeff. *(t-stat)*	Coeff. *(t-stat)*
C	-0.650	-0.197	-1.070
	(-0.541)	*(-0.173)*	*(-0.886)*
ΔF_{t-1}	-0.069	0.052	-0.119
	(-1.225)	*(0.840)*	*(-1.205)*
R_{t-1}	-76.264	-35.701	**-134.978****
	(-1.717)	*(-0.881)*	*(-2.323)*
i_{t-1}	14.042	49.234	24.183
	(0.157)	*(0.711)*	*(0.395)*
ys_{t-1}	0.425	-0.003	-0.074
	(0.703)	*(0.004)*	*(0.154)*
$basis_{t-1,T}$	0.055	0.011	-0.024
	(1.627)	*(0.286)*	*(-0.736)*
R^2	**0.023**	**0.015**	**0.046**
Adj. R^2	**-0.001**	**-0.011**	**0.009**

Table 3.2: Forecasting with the economic variables model: In-sample analysis. The entries report results from the regression of each VIX futures series on a set of lagged economic variables, augmented by an AR(1) term. The following specification is estimated: $\Delta F_{t,T} = c + a_1 \Delta F_{t-1,T} + a_2 R_{t-1} + a_3 i_{t-1} + a_4 ys_{t-1} + a_5 basis_{t-1,T} + \varepsilon_{t,T}$, where $\Delta F_{t,T}$: daily changes in the futures prices between time *t-1* and *t* for a given maturity *T*, *c*: a constant, R_t: the log-return on the S&P 500 stock index between time *t-1* and *t*, i_t: the one month Libor rate in log-differences , ys_t: the slope of the yield curve calculated as the difference between the prices of the ten year U.S. government bond and the one-month interbank rate, and $basis_{t,T}$: the difference at any time *t* between the VIX index and the VIX futures price for a given maturity *T*. The estimated coefficients, Newey-West *t*-statistics in parentheses, the unadjusted R^2 and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The model has been estimated for the period March 26, 2004 to March 17, 2005.

	Dependent Variable: **Shortest**	Dependent Variable: **2nd Shortest**	Dependent Variable: **3rd Shortest**
	Coeff. *(t-stat)*	Coeff. *(t-stat)*	Coeff. *(t-stat)*
Panel A: AR(2) Model			
Included Obs.	204	191	95
c	-0.465	-0.426	-0.513
	(-1.485)	*(-1.590)*	*(-1.638)*
φ_1	0.034	0.119**	0.021
	(0.746)	*(1.986)*	*(0.280)*
φ_2	-0.085	-0.124	-0.089
	(-1.565)	*(-1.542)*	*(-1.048)*
R^2	**0.010**	**0.029**	**0.009**
Adj. R^2	**0.001**	**0.019**	**-0.008**
Panel B: VAR Model			
Included Obs.	**130**	**130**	**130**
C	-0.524	-0.505	-0.306
	(-1.343)	*(-1.752)*	*(-0.992)*
$\Delta F1_{t-1}$	-0.161	-0.134	-0.121
	(-0.986)	*(-1.113)*	*(-0.941)*
$\Delta F2_{t-1}$	**0.425****	**0.311****	**0.358****
	(1.987)	*(1.970)*	*(2.120)*
$\Delta F3_{t-1}$	-0.071	0.005	-0.149
	(-0.289)	*(0.028)*	*(-0.766)*
R^2	**0.043**	**0.053**	**0.037**
Adj. R^2	**0.020**	**0.031**	**0.014**
Panel C: ARMA(1,1) Model			
Included Obs.	226	217	156
c	**-0.042***	-0.373	-0.722
	(-3.875)	*(-0.909)*	*(-1.402)*
φ_1	**0.854***	**(-0.558)**	-0.579
	(25.652)	*(-2.352)*	*(-0.890)*
θ_1	**-0.992***	**0.679***	0.652
	(-161.116)	*(3.057)*	*(1.062)*
R^2	**0.064**	**0.023**	**0.007**
Adj. R^2	**0.055**	**0.014**	**-0.006**

Table 3.3: Forecasting with the univariate autoregressive, ARMA and VAR models: In-sample analysis. Panel A: The entries report results from the estimation of a univariate AR(2) specification for the daily changes of each VIX futures series, namely: $\Delta F_{t,T} = c + \varphi_1 \Delta F_{t-1,T} + \varphi_2 \Delta F_{t-2,T} + \varepsilon_{t,T}$. **Panel B:** The entries report the estimated coefficients of a VAR, for the three VIX futures prices series: $\Delta F_t = C + \Phi_1 \Delta F_{t-1} + \varepsilon_t$, where ΔF_t is the (3x1) vector of changes in the three futures prices series, C is a (3x1) vector of constants, Φ_1 is the (3x3) matrix of coefficients to be estimated, and ε_t is a (3x1) vector of errors. **Panel C:** The entries report the estimated coefficients of a ARMA(1,1) model: $\Delta F_{t,T} = c + \varphi_1 \Delta F_{t-1,T} + \theta_1 \varepsilon_{t-1,T} + \varepsilon_{t,T}$. The estimated coefficients, Newey-West *t*-statistics in parentheses, the unadjusted R^2 and adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The models have been estimated for the period March 26, 2004 to March 17, 2005.

	Shortest	2nd Shortest	3rd Shortest
	Panel A: Random Walk		
RMSE	7.01	5.16	4.55
MAE	4.32	3.31	2.89
	Panel B: Economic Variables Model		
RMSE	7.18	5.25	4.70
MAE	**4.44****	**3.42****	**3.03****
MCP	**54.67%**$^{+}$	47.35%	50.94%
	Panel C: AR(2) Model		
RMSE	7.26	5.37	4.81
MAE	4.45	3.46	3.09
MCP	**54.78%**$^{+}$	51.66%	52.81%
	Panel D: VAR(1) Model		
RMSE	7.60	5.49	4.77
MAE	4.74	3.56	3.06
MCP	52.92%	49.74%	53.36%
	Panel E: ARMA(1,1) Model		
RMSE	**7.17****	5.23	4.68
MAE	4.34	3.35	2.98
MCP	**55.44%**$^{+}$	50.55%	52.43%
	Panel F: Equally Weighted Combination Forecast		
RMSE	7.71	5.55	4.92
MAE	4.82	3.63	3.18
MCP	**53.55%**$^{++}$	49.07%	51.37%
	Panel G: Weighted Combination Forecast		
RMSE	7.77	**5.60****	4.96
MAE	4.90	**3.67****	3.21
MCP	50.09%	50.19%	50.00%

Table 3.4: Out-of-sample performance of the model specifications for each one of the VIX futures prices series. The root mean squared prediction error (RMSE), mean absolute prediction error (MAE), and mean correct prediction (MCP) of the direction of change in the value of each VIX futures price series are reported. The random walk model (Panel A), the economic variables model (Panel B), the AR(2) model (Panel C), the VAR model (Panel D), and the ARMA(1,1) model (Panel E) have been implemented. Results for the equally weighted and weighted combination point forecasts (Panel F and G, respectively) are also reported. The Modified Diebold-Mariano test (for RMSE and MAE) based on a Newey-West estimator of the variance of $\overline{d}_T^{\,i}$ and the ratio test (for MCP) are employed, to test the null hypothesis that the random walk and the model under consideration perform equally well. Two alternative hypotheses H_1 and H_2 are considered. Namely H_1: the random walk outperforms the model and H_2: the model outperforms the random walk. One and two asterisks (crosses) denote rejection of the null hypothesis in favour of the alternative H_1 (H_2) at significance levels 1% and 5%, respectively. The models have been estimated recursively for the period March 18, 2005 to March 13, 2008.

	Shortest		2nd Shortest		3rd Shortest	
Interval Forecasts	**99%**	**95%**	**99%**	**95%**	**99%**	**95%**
Panel A: Economic Variables Model Interval Forecasts						
# Violations	3.16%	9.79%	2.41%	9.15%	3.09%	8.75%
LR_{unc}	**19.96***	**25.37***	**8.95***	**18.33***	**16.50***	**14.23***
Panel B: AR(2) Model Interval Forecasts						
# Violations	3.24%	9.88%	2.98%	8.94%	3.63%	9.26%
LR_{unc}	**20.67***	**25.58***	**15.63***	**16.16***	**22.98***	**16.98***
Panel C: VAR(1) Model Interval Forecasts						
# Violations	2.92%	10.14%	4.01%	10.47%	3.89%	9.19%
LR_{unc}	**14.30***	**25.25***	**29.92***	**27.84***	**27.54***	**16.93***
Panel D: ARMA(1,1) Model Interval Forecasts						
# Violations	3.38%	10.00%	2.50%	9.86%	3.18%	9.05%
LR_{unc}	**24.05***	**28.09***	**10.30***	**25.07***	**18.22***	**16.77***
Panel E: Equally Weighted Combination Interval Forecasts						
# Violations	2.91%	10.75%	2.61%	10.45%	4.10%	9.77%
LR_{unc}	**13.41***	**29.14***	**9.74***	**25.85***	**28.02***	**19.39***
Panel F: Weighted Combination Interval Forecasts						
# Violations	2.91%	9.65%	3.17%	10.26%	3.32%	9.18%
LR_{unc}	**13.41***	**19.91***	**16.22***	**24.27***	**17.32***	**15.27***

Table 3.5: Statistical efficiency of the bootstrapped interval forecasts. Entries report the percentage of the observations that fall outside the bootstrapped intervals, and the values of Christoffersen's (1998) likelihood ratio test of unconditional coverage (LR_{unc}) for each VIX futures price series. The null hypothesis is that the percentage of times that the actually realized futures price falls outside the constructed (1-α)%-interval forecasts is a%. One and two asterisks denote rejection of the null hypothesis at 1% and 5% significance levels, respectively. The results are reported for daily 99% and 95%-interval forecasts generated by the economic variables model (Panel A), AR(2) model (Panel B), VAR model (Panel C) and ARMA(1,1) model (Panel D). Results for the equally weighted and weighted combination 99% and 95%-interval forecasts (Panel E and F, respectively) are also presented. The models have been estimated recursively for the period March 18, 2005 to March 13, 2008.

	Shortest	2^{nd} Shortest	3^{rd} Shortest
Panel A: Economic Variables Model Point Forecasts			
Sharpe Ratio	0.085	0.013	-0.015
95% CI	*(0.02,0.14)*	*(-0.07, 0.09)*	*(-0.09, 0.06)*
Leland's Alpha	0.854	0.104	-0.101
95% CI	*(0.21, 1.51)*	*(-0.46, 0.69)*	*(-0.59, 0.40)*
Panel B: AR(2) Model Point Forecasts			
Sharpe Ratio	0.017	-0.013	-0.031
95% CI	*(-0.05, 0.09)*	*(-0.08, 0.06)*	*(-0.11, 0.05)*
Leland's Alpha	0.167	-0.071	-0.181
95% CI	*(-0.58, 0.92)*	*(-0.57, 0.49)*	*(-0.63, 0.32)*
Panel C: VAR(1) Model Point Forecasts			
Sharpe Ratio	-0.018	-0.039	0.048
95% CI	*(-0.11, 0.07)*	*(-0.11, 0.04)*	*(-0.03, 0.12)*
Leland's Alpha	-0.170	-0.270	0.300
95% CI	*(-1.1, 0.68)*	*(-0.88, 0.27)*	*(-0.18, 0.78)*
Panel D: ARIMA(1,1,1) Model Point Forecasts			
Sharpe Ratio	0.013	-0.007	-0.016
95% CI	*(-0.07, 0.10)*	*(-0.09, 0.07)*	*(-0.09, 0.06)*
Leland's Alpha	0.138	-0.034	-0.095
95% CI	*(-0.69, 0.89)*	*(-0.68, 0.53)*	*(-0.47,0.39)*
Panel E: Equally Weighted Point Forecasts			
Sharpe Ratio	0.020	-0.019	-0.033
95% CI	*(-0.06, 0.11)*	*(-0.10, 0.06)*	*(-0.11, 0.04)*
Leland's Alpha	0.196	-0.120	-0.195
95% CI	*(-0.53, 0.91)*	*(-0.67, 0.52)*	*(-0.66,0.31)*
Panel F: Weighted Point Forecasts			
Sharpe Ratio	-0.011	-0.050	-0.073
95% CI	*(-0.08, 0.06)*	*(-0.13, 0.02)*	*(-0.13, -0.01)*
Leland's Alpha	-0.104	-0.343	-0.447
95% CI	*(-0.81, 0.57)*	*(-0.93, 0.26)*	*(-0.83, -0.04)*

Table 3.6: Trading strategy with VIX futures based on point forecasts from March 18, 2005 to March 13, 2008. The entries show the annualised Sharpe ratio (SR) and Leland's (1999) alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% *CI*) within parentheses. The stationary bootstrap of Politis and Romano (1994) has been employed. The strategy is based on point forecasts obtained from the economic variables model (Panel A), the AR(2) model (Panel B), the VAR model (Panel C) and the ARMA(1,1) model (Panel D). Results for the equally weighted and the weighted combination point forecasts (Panel E and F respectively) are also reported. The SR for a naïve buy and hold strategy in VIX volatility futures is 0.0178 [95% CI = (-0.07, 0.08)] for the shortest maturity series, 0.0421 [95% CI = (-0.02, 0.10)] for the second shortest maturity series and 0.0532 [95% CI = -0.01, 0.12)] for the third shortest maturity series.

Interval Forecasts	Shortest 99%	Shortest 95%	2nd Shortest 99%	2nd Shortest 95%	3rd Shortest 99%	3rd Shortest 95%
Panel A: Economic Variable Model Interval Forecasts						
Sharpe Ratio	0.020	-0.001	0.036	0.034	0.007	0.029
95% CI	*(-0.05, 0.08)*	*(-0.08, 0.06)*	*(-0.02, 0.10)*	*(-0.03, 0.10)*	*(-0.07, 0.08)*	*(-0.03, 0.09)*
Leland's Alpha	0.194	-0.014	0.267	0.244	0.050	0.181
95% CI	*(-0.50, 0.91)*	*(-0.67, 0.64)*	*(-0.20, 0.73)*	*(-0.24, 0.73)*	*(-0.43, 0.54)*	*(-0.21, 0.59)*
Panel B: AR(2) Model Interval Forecasts						
Sharpe Ratio	0.018	0.016	0.018	0.044	0.063	0.035
95% CI	*(-0.04, 0.08)*	*(-0.05, 0.07)*	*(-0.05,0.08)*	*(-0.02, 0.11)*	*(-0.01, 0.13)*	*(-0.03, 0.10)*
Leland's Alpha	0.178	0.163	0.131	0.321	0.395	0.224
95% CI	*(-0.44, 0.82)*	*(-0.42, 0.76)*	*(-0.35, 0.61)*	*(-0.16, 0.80)*	*(-0.08, 0.84)*	*(-0.23, 0.67)*
Panel C: VAR(1) Model Interval Forecasts						
Sharpe Ratio	0.035	0.014	0.026	0.010	0.034	0.026
95% CI	*(-0.03,0.09)*	*(-0.05, 0.07)*	*(-0.04, 0.09)*	*(-0.06, 0.07)*	*(-0.05,0.11)*	*(-0.04, 0.10)*
Leland's Alpha	0.346	0.142	0.183	0.080	0.210	0.167
95% CI	*(-0.23, 0.96)*	*(-0.41, 0.70)*	*(-0.32, 0.63)*	*(-0.39, 0.55)*	*(-0.19, 0.67)*	*(-0.25, 0.65)*
Panel D: ARMA(1,1,1) Model Interval Forecasts						
Sharpe Ratio	0.025	0.022	0.054	0.034	0.038	0.032
95% CI	*(-0.04, 0.08)*	*(-0.04, 0.09)*	*(-0.02, 0.12)*	*(-0.03, 0.10)*	*(-0.03, 0.11)*	*(-0.04, 0.10)*
Leland's Alpha	0.246	0.220	0.390	0.249	0.236	0.196
95% CI	*(-0.34, 0.93)*	*(-0.38, 0.87)*	*(-0.14, 0.84)*	*(-0.26, 0.75)*	*(-0.18, 0.68)*	*(-0.22, 0.64)*
Panel E: Equally Weighted Combination Interval Forecasts						
Sharpe Ratio	0.029	0.019	0.033	0.034	0.036	0.025
95% CI	*(-0.03, 0.09)*	*(-0.04, 0.07)*	*(-0.03, 0.09)*	*(-0.03, 0.10)*	*(-0.03, 0.10)*	*(-0.05,0.10)*
Leland's Alpha	0.288	0.191	0.240	0.251	0.223	0.162
95% CI	*(-0.33, 0.91)*	*(-0.35, 0.77)*	*(-0.25, 0.70)*	*(-0.23, 0.75)*	*(-0.16, 0.62)*	*(-0.31, 0.62)*
Panel F: Weighted Combination Interval Forecasts						
Sharpe Ratio	-0.016	0.017	0.061	0.031	0.013	0.031
95% CI	*(-0.08, 0.04)*	*(-0.05, 0.08)*	*(-0.004, 0.12)*	*(-0.03, 0.09)*	*(-0.06, 0.08)*	*(-0.04, 0.10)*
Leland's Alpha	-0.159	0.171	0.439	0.222	0.085	0.191
95% CI	*(-0.79, 0.44)*	*(-0.50, 0.82)*	*(-0.03, 0.95)*	*(-0.25, 0.66)*	*(-0.36, 0.53)*	*(-0.24, 0.63)*

Table 3.7: Trading strategy with VIX futures based on bootstrapped interval forecasts from March 18, 2005 to March 13, 2008. The entries show the annualised Sharpe ratio (SR), Leland's (1999) alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% *CI*) within parentheses. The stationary bootstrap of Politis and Romano (1994) has been employed. The strategy is based on 99% and 95%-bootstrapped interval forecasts obtained from the economic variables model (Panel A), the AR(2) model (Panel B), the VAR model (Panel C) and the ARMA(1,1) model (Panel D). Results for the equally weighted and the weighted combination point forecasts (Panel E and F respectively) are also reported. The SR for a naïve buy and hold strategy in VIX volatility futures is 0.0178 [95% CI = (-0.07, 0.08)] for the shortest maturity series, 0.0421 [95% CI = (-0.02, 0.10)] for the second shortest maturity series and 0.0532 [95% CI = -0.01, 0.12)] for the third shortest maturity series.

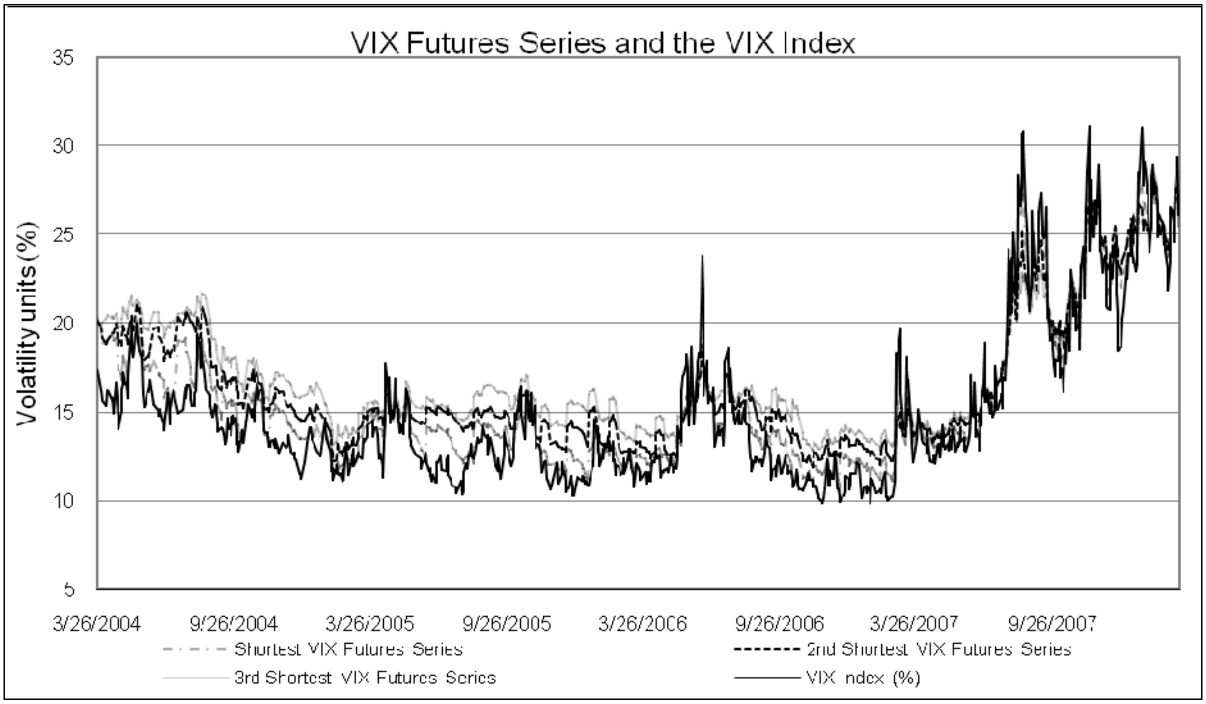

Figure 3.1: Evolution of the three shortest maturity VIX futures series and the VIX index over the period March 26, 2004 to March 13, 2008.

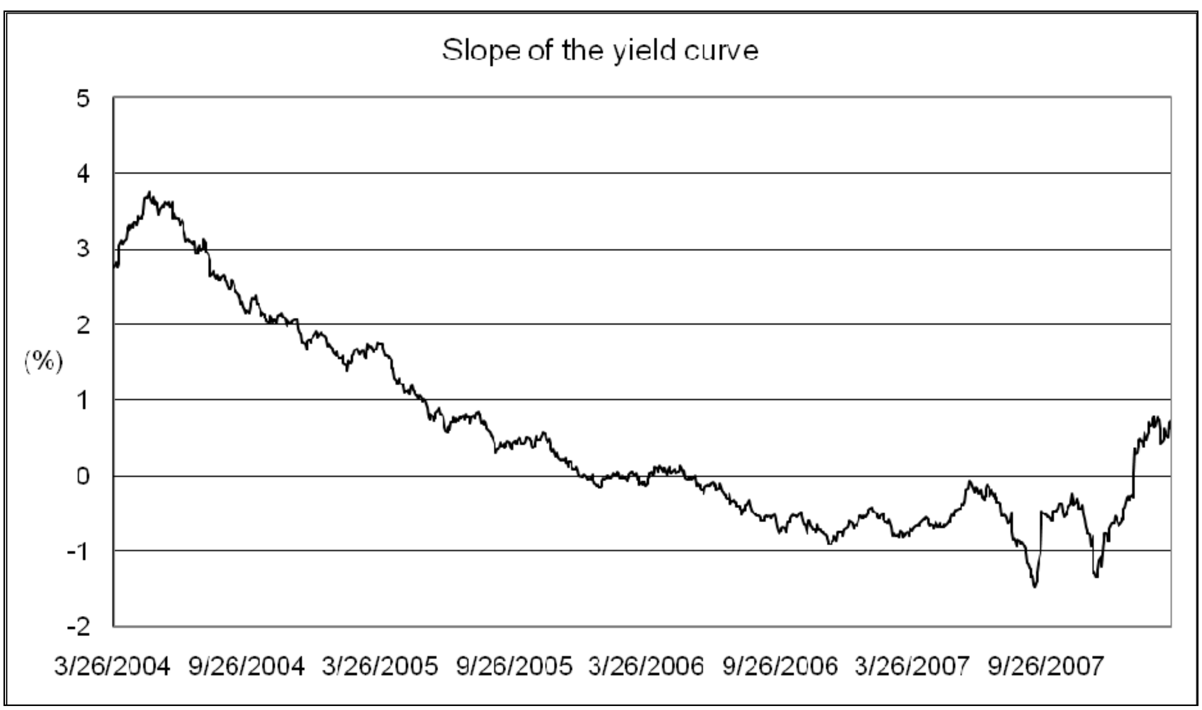

Figure 3.2: Evolution of the slope of the yield curve over the period March 26, 2004 to March 13, 2008. The slope of the yield curve is calculated as the difference between the prices of the ten year U.S. government bond and the one month interbank rate.

Chapter 4: The impact of news announcements on volatility spillovers - International evidence from implied volatility markets

Abstract

This paper investigates the role of scheduled news announcements in explaining the transmission of volatility, both within European markets and across U.S. and European ones. To this end, a novel approach is taken by employing a set of widely followed implied volatility indices. Aggregate, regional, and individual event dummies and surprise measures for U.S. and European news announcements are constructed. We find that implied volatility spillovers exist between U.S. and European markets and within European countries. Furthermore, these volatility linkages continue to show up even after the effect of news announcements is taken into account. In this case, aggregate and regional releases account partially for the reported volatility spillovers. Finally, aggregate and regional releases affect also the magnitude of volatility spillovers when their content is considered. These findings are consistent with the market efficiency hypothesis for option markets.

1. Introduction

The Crash of October 1987 has motivated the growth of a vast literature that explores the transmission of volatility across stock markets (see Gagnon and Karolyi, 2006, for an extensive review). Surprisingly, the role of news announcements to explain these volatility linkages empirically has received limited attention.[19] This paper ties together the volatility spillover and news announcement literature by examining whether (1) shocks in volatility are transmitted both between U.S. and European stock markets and within European ones, (2) news announcements account for the reported volatility spillovers, and (3) news announcements affect the magnitude of volatility spillovers, i.e. whether volatility spillovers

[19] Despite the fact that the research on the effect on news announcements on volatility spillovers is limited, there is an extensive boady of literature that has investigated the effect of news announcements on various financial variables, such as stock prices [see e.g., Hardouvelis (1987a)], exchange rates [see e.g., Hardouvelis (1988)], interest rates [see e.g., Hardouvelis (1987b, 1988)].

are significantly different on announcement days as opposed to non-announcement days. The answer to these questions is of particular importance to both academics and practitioners for at least four reasons. First, the documentation of volatility spillovers has implications for the integration of markets within and across regions (see e.g., Bekaert et al., 2005, and references therein). Second, understanding how volatility shocks transmit from one market to another is important for international portfolio management and portfolio diversification purposes. Third, in the case where volatility spillovers continue to show up even after "fundamental" news announcements have been taken into account, this will have implications for the existence of volatility contagion (see Pericoli and Sbracia, 2003, for the various definitions of contagion). Fourth, the existence of volatility spillovers and their relationship to news announcements has implications for markets efficiency. For instance, in the case where volatility is transmitted across markets in a systematic way around scheduled news announcements, it may be possible to devise profitable option trading strategies (see e.g., Donders and Vorst, 1996, Ederington and Lee, 1996).

To the best of our knowledge, Becker et al. (1995) and Connolly and Wang (1998) are the only related studies to this paper. Their analysis is backward-looking in the sense that their volatility measures rely on historical data (high frequency asset returns and conditional volatility models, respectively). Instead, we examine the impact of news announcements on volatility spillovers by employing *implied volatility* to measure the expected stock market volatility. Implied volatility, by definition, is a forward-looking measure of market volatility (see e.g., Granger and Poon, 2003, for a review of the literature on the information content of implied volatility) and is easily extracted from the option market prices. In particular, to address our three main questions, major implied volatility indices widely followed by academics and practitioners are employed. More specifically, we use six European and three U.S. implied volatility indices that are constructed in a model-free way and enable capturing the volatility of the respective stock markets (see Jiang and Tian, 2005, Carr and Wu, 2006 and the CBOE VIX white paper).[20] The value of an implied volatility index represents the implied volatility of a synthetic option that has constant time-to-maturity at every point in time. In addition, they are more informative than the implied volatility of a single option

[20] The CBOE white paper can be retrieved from http://www.cboe.com/micro/vix/vixwhite.pdf.

contract, since they take into account the information contained in option prices across the whole spectrum of strike prices. Furthermore, using implied volatility indices is advantageous because they are not subject to the considerable measurement errors that implied volatilities are notorious for since they use information from out-of-the money options (see Hentschel, 2003). The use of U.S. and European implied volatility indices will also allow us detecting the importance of the two regions in explaining implied volatility spillovers, i.e. whether there is a European (U.S.) regional effect where Eurozone (U.S.) volatility drives European and U.S. volatility indices.

A number of studies have already documented the transmission of implied volatility across international markets (see e.g., Gemmill and Kamiyama, 2000, Aboura, 2003, Skiadopoulos, 2004, Nikkinen et al., 2006). From a theoretical point of view, news releases are expected to affect volatility; Ross (1989) showed that in the absence of arbitrage ,the instantaneous variance of returns equals the variance of information flow. In addition, the empirical evidence has documented that implied volatility drops as soon as a scheduled news announcement is released (see e.g., Patell and Wolfson, 1979, Donders and Vorst, 1996, Ederington and Lee, 1996, Fornari and Mele, 2001, Kim and Kim, 2003, Fornari, 2004, for an examination of at-the-money implied volatility, and Steeley, 2004, Beber and Brandt, 2006, Äijö, 2008, for an examination of the second moment of option implied risk-neutral distributions).[21] This finding is consistent with the models of implied volatility behavior around scheduled news announcements suggested by Patell and Wolfson (1979), and Ederington and Lee (1996) that predict that implied volatility falls on scheduled news announcement days.[22] A similar reaction to scheduled news announcements has also been

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[21] In the case of scheduled news announcements, the timing but not the content of the release is known a priori by market participants. There is also some literature that considers unscheduled news announcements (i.e. neither the timing nor the content are known a priori by market participants); implied volatility is found to increase on unscheduled announcement days (see e.g., Ederington and Lee, 1996, Fornari and Mele, 2001).

[22] Both models predict that implied volatility increases gradually prior to a news release and falls on the announcement. This prediction is based on the interpretation of implied volatility as the average volatility expected until the expiration of the option (see Hull and White, 1987), a set of further assumptions and a shrinking time to maturity. Thus, this prediction does not hold for implied volatility indices that have a constant time to maturity at every point in time. However, both models can be extended so as to accommodate a constant time to maturity, but unambiguous expectations cannot be made without making any additional restrictive assumptions. Note also that in the case of conditional volatility the reverse behavior is anticipated, namely conditional volatility is expected to be low before an important release occurs and then increase on the announcement (see Cenesizoglu, 2009, for a theoretical explanation). This is line with the empirical evidence

documented in an implied volatility index setting (see e.g., Nikkinen and Sahlström, 2001, 2004a, and Chen and Clements, 2007). However, none of these studies has investigated the effect of news announcements to the reported volatility spillovers; their analysis is constrained in a single-country setting.

In contrast to the previous literature, we investigate the impact of news announcements on implied volatility spillovers; a broad set of European and U.S. implied volatility indices and scheduled news releases is employed. To the best of our knowledge, this approach is novel and makes at least six contributions to the existing literature. First, it allows understanding whether implied volatility spillovers are preserved even after the effect of news announcements has been taken into account. Second, it sheds light on whether releases affect the magnitude of implied volatility spillovers. Third, we identify whether there are regional European or U.S. effects. This is analogous to the literature that attributes a country's volatility to three separate components, namely the local (i.e. own-country), the regional (i.e. own-region) and the world (usually the U.S. is used as a proxy of the world) component (see e.g., Baele, 2005, Bekaert et al., 2005, Asgharian and Nossman, 2008). This literature has found mixed results, in the sense that the regional component is more important in some cases (see e.g., Bekaert et al., 2005, Asgharian and Nossman, 2008) and the U.S. component dominates in some other (see e.g., Baele, 2005). Fourth, we examine the impact of both U.S. and European release items; the literature on the effect of news announcements on implied volatility has considered that of either U.S. or European releases, separately.[23] In addition, the use of various U.S. and European release items enables detecting their respective individual as well as aggregate impact on the dynamics of implied volatility indices. Previous studies have primarily focused on examining the effect of individual releases on volatility, with the exception of Nofsinger and Prucyk (2003) and de Goeij and Marquering (2006) who employed aggregate news announcements within a single-country setting. Fifth, we investigate the announcement and surprise effect of the releases within a volatility spillover

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reported on the conditional volatility in bond markets, termed the "calm-before-the-storm" effect by Jones et al. (1998).

[23] Nikkinen and Sahlström (2004b) and Äijö (2008) are the only studies that have considered the effect of both European and U.S. releases on implied voaltility. The former study has found that only the U.S. news announcements exert a significant impact on implied volatility, while the latter documents that both the European and the U.S. announcements affect implied volatility.

framework.[24] Examining these two types of effect has interesting implications regarding market efficiency. This is because the market efficiency hypothesis (see Fama, 1970, 1991) dictates that financial markets should react only to the unexpected component of news announcements. Hence, evidence of a surprise effect would be consistent with this theory. On the other hand, evidence for an announcement effect but not a surprise one would not support the notion of market efficiency. Sixth, the current study adds to the literature on the predictability of implied volatility [see Chapter 2 and the references therein]. This is because understanding the way implied volatility is transmitted across markets and the role of news announcements may help constructing potentially superior implied volatility forecasts.

The rest of the paper is structured as follows. The following section describes the dataset. In Section 3, the research methodology and the results pertinent to implied volatility spillovers are presented. The extent to which implied volatility spillovers are preserved once the announcement and surprise effect of aggregate regional and individual news announcements has been taken into account is explored in Section 4. Section 5 examines the impact of aggregate and regional news announcements on the magnitude of implied volatility spillovers. The final section concludes and discusses the implications of the findings.

2. Data

The data consist of daily closing prices of nine implied volatility indices and the news announcements for a set of economic variables obtained from Bloomberg. The sample spans the period from February 2, 2001 to January 8, 2010, so as to study all indices over a common time period.

Three U.S. (VIX, VXN and VXD) and six European (VDAX-NEW, VCAC VAEX, VBEL, VSMI and VSTOXX) implied volatility indices are considered. Some of the previous studies have examined the reaction of financial market volatility to news announcements by using intra-day data (see e.g., Chen et al., 1999, for an examination of stock market volatility,

[24] In the case of the *announcement effect*, only the timing of the releases is considered and news announcements are modeled merely as events. In the case of the *surprise effect*, the timing as well as the content of the releases is taken into account and news announcements are measured by their unexpected component (i.e. surprise element). A similar terminology has been used in the literature. More specifically, Beber and Brandt (2006) use the terms unconditional and conditional response for the announcement and the surprise effect, respectively, and Christiansen and Ranaldo (2007) use the terms announcement and news effect.

Ederington and Lee, 1993, for an examination of interest rate and foreign exchange volatility). We focus instead on the daily closing prices of the implied volatility indices under consideration This is because closing prices capture the "leakages" (if any) of the announcement information prior to the actual release (see Birru and Figlewski, 2010) as well as the adjustment of volatility to its equilibrium level after the occurrence of the announcement (see Ehrmann and Fratzscher, 2005, and Birru and Figlewski, 2010). The U.S. stock index option markets close at 4:15pm Eastern Time (ET) and the European stock index option markets close at 11:30 am ET (see Figure 4.1).

The construction algorithm of all implied volatility indices is based on the concept of model-free implied variance proposed by Britten-Jones and Neuberger (2000).[25] The indices represent the 30-day variance swap rate once they are squared (see Carr and Wu, 2006, and the references therein).[26] VIX, VXN, and VXD are extracted from the market prices of options on the S&P 500, Nasdaq 100, and Dow Jones Industrial Average (DJIA) index, respectively. VDAX-New, VCAC, VAEX, VBEL, VSMI and VSTOXX are constructed from the market prices of options on the DAX (Germany), the CAC 40 (France), the AEX (Netherlands), the BEL 20 (Belgium), the SMI (Switzerland) and the DJ EURO STOXX 50 index, respectively. The data for all the implied volatility indices are obtained from Bloomberg.

Table 4.1 shows the summary statistics of the implied volatility indices (in levels and first differences, Panels A and B, respectively). The first order autocorrelation ρ1, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. We can see that none of the implied volatility indices is normally distributed either in levels or in first differences. In addition, most indices exhibit strong autocorrelation in the levels and in the first differences. Finally, the values of the ADF test show that implied volatility indices are non-stationary in the levels, and stationary in the first differences (see also Dotsis et al., 2007, for a study on the dynamics of various implied volatility indices).

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[25] The construction algorithm of all implied volatility indices is based on the concept of the fair value of the variance swap rate suggested by Demeterfi et al. (1999a, 1999b). Jiang and Tian (2007) have shown that this concept is equivalent to the model-free implied variance.

[26] A variance swap is a forward contract on annualized variance; the buyer (seller) of the contract receives the difference between the realized variance of the returns of a stated index and a fixed variance rate, termed variance swap rate, if the difference is positive (negative).

Twelve U.S. and eight European scheduled news announcement items are also employed in our study. The exact timing of the releases and their corresponding survey forecasts are obtained from Bloomberg.[27] Every Friday, Bloomberg surveys key financial institutions for their forecasts regarding the values of economic variables that will be released within the next week. The median of the responses is considered as the survey forecasted value for the respective economic variable (see Vähämaa et al., 2005). The U.S. economic variables under consideration are the change in non-farm payrolls (NFP), the consumer confidence index (CCI), the consumer price index (CPI), the durable goods orders (DGO), the FOMC rate decision (FOMC), the gross domestic product (GDP), the initial jobless claims (IJC), the ISM non-manufacturing (ISM), the leading indicators (LI), the new home sales (NHS), the producer price index (PPI), and the retail sales less autos (RS). The European news announcement types include the ECB interest rate (ECB), the Euro-zone consumer confidence index (EU-CCI), the Euro-zone consumer price index (EU-CPI), the Euro-zone gross domestic product (EU-GDP), the Euro-zone producer price index (EU-PPI), the Euro-zone retail sales (EU-RS), the IFO business climate (IFO), and the ZEW survey (ZEW). The various news announcement items are briefly defined in Table 4.2.

Table 4.3 reports the source, timing, frequency, units of measurement and total number (N) of the news announcements in our sample. We can see that most news announcement items are reported on a monthly basis. The only exceptions are the initial jobless claims announcement that is released every week, and the FOMC rate decision and the ECB interest rate announcements (eight and eleven times per annum, respectively). In addition, all but one releases included in our sample occur before the U.S. option markets close on day *t* (i.e. before 4:15pm ET).[28] Furthermore, most of the announcements occur

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[27] In general, the Bloomberg survey forecasts have been found to be rational (see Switzer and Noel, 2001). Similar findings have also been documented for the Money Market Services International (MMS) survey forecasts (see e.g., Campbell and Sharpe, 2009). MMS survey forecasts have been used frequently in previous studies (see e.g., Beber and Brandt, 2006). However, we prefer using the Bloomberg forecasts for two reasons. First, MMS forecasts are not available for Euro-zone news announcements. In addition, it is not clear whether the methodology of their construction has changed since 2003. This is because, MMS was acquired by Informa Group plc in 2003 and does not provide survey forecasts any longer. Instead, the survey forecasts for the U.S. news announcements are provided by Action Economics llc (see also Brenner et al., 2009, for a discussion along these lines).

[28] The only exception is one out of the 466 initial jobless claims announcements that occurs at 10:30pm ET.

before the European option markets close (i.e. before 11:30am ET). All but one releases that occur after the closing of the European option markets on day *t* refer to the FOMC rate decision. Note that in the case where an announcement occurs on day *t* before the markets close, this release will have an impact on the changes of the implied volatility indices between *t*-1 and *t*. On the other hand, if an announcement occurs on day *t* after the markets close, then this release will have an impact on the changes of the implied volatility indices between *t* and *t+1*. This will be taken into account to measure the related variables that will be employed in the specifications described in Section 3.

3. Implied volatility spillovers

We begin our analysis by investigating whether implied volatility is transmitted across markets. So, hypothesis *H1a* is formulated:

H1a: *Implied volatility spillovers do not exist between countries.*

To test *H1a* we estimate a standard VAR(1) model, i.e.

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + \varepsilon_t \tag{4.1}$$

where $\Delta IV_t = IV_t - IV_{t-1}$ is the (9x1) vector of changes in the implied volatility indices between *t*-1 and *t*, *C* is a (9x1) vector of constants, Φ is a (9x9) matrix of coefficients, and ε is a (9x1) vector of residuals. The number of lags has been chosen so as to minimize the BIC criterion and keep the model parsimonious. Previous studies have also employed a VAR modeling framework to investigate the presence of implied volatility spillovers (see e.g., Gemmill and Kamiyama, 2000, Aboura, 2003, Skiadopoulos, 2004, Nikkinen et al., 2006).

Table 4.4 shows the estimated coefficients, t-statistics and adjusted R2 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. We can see that *H1a* is rejected, since there is evidence that implied volatility is transmitted between and within regions. In particular, implied volatility is transmitted from U.S. to Europe, since the lagged changes in VIX and VXN have a significant impact on most the European volatility indices. In addition, all U.S. volatility indices are significantly affected by the lagged changes in VDAX, VCAC and VSMI. Thus, implied volatility also spills over from Europe to the US. Furthermore, there are some effects within regions, as lagged changes in VSTOXX are significant for all European indices apart from VAEX. Finally, the adjusted R^2 is generally greater for the European implied volatility indices than for the U.S. ones and takes the largest value for the VSMI (22%) and the lowest for the VXN (3.7%). These findings are consistent with the Engle et al. (1990) who document the presence of "meteor showers" (i.e. volatility spillovers across markets) in foreign exchange markets.

Next, we investigate whether there is a European (U.S.) regional effect, i.e. whether Eurozone (U.S.) volatility drives European and U.S. volatility indices. To this end, *H1a* is appropriately modified:

H1b: *There is no U.S. and/or European effect.*

To examine the significance of the U.S. and the European effect, a univariate regression setting is employed. More specifically, in the case of the *U.S. implied volatility indices H1b* is tested by estimating the following specification:

$$\Delta IV_{i,t} = c_i + \varphi_i \Delta IV_{i,t-1} + \alpha_i^{EU} PC_{i,t-1}^{EU} + \varepsilon_{i,t} \tag{4.2}$$

where $\Delta IV_{i,t} = IV_{i,t} - IV_{i,t-1}$ is the change in the *i*-th implied volatility index between *t*-1 and *t* (*i* = 1 for VIX, 2 for VXN, 3 for VXD) and $PC_{i,t-1}^{EU}$ is the lagged first principal component extracted from applying principal component analysis (PCA) to the set of all European implied volatility indices. The employed PC takes into account the presence of any spillover effects from Europe to the U.S. and captures the European effect, while the lagged implied volatility index captures the U.S. effect. Hence, the null hypothesis to be tested is *H1b*: $\varphi_i = a_i^{EU} = 0$ for *i* = 1, 2, 3. In the case of the *European implied volatility indices*, we estimate the following specification:

$$\Delta IV_{i,t} = c_i + \varphi_i \Delta IV_{i,t-1} + \alpha_i^{US} PC_{i,t-1}^{US} + \alpha_i^{EU} PC_{i,t-1}^{EU} + \varepsilon_{i,t} \tag{4.3}$$

where *i* = 4 (for VDAX), 5 (for VCAC), 6 (for VAEX), 7 (for VBEL), 8 (for VSMI), 9 (for VSTOXX) and $PC_{i,t-1}^{r}$ is the lagged first principal component extracted from applying PCA to the set of implied volatility indices of region *r* (*r* = 1 for the U.S. and *r* = 2 for European indices) where the *i*-th implied volatility index is excluded from this set. The $PC_{i,t-1}^{US}$ ($PC_{i,t-1}^{EU}$)

takes into account the presence of spillovers from U.S. (from the remaining European implied volatility indices) to the *i*-th European implied volatility index and captures the U.S. effect (European effect). [29] This implies that the null hypothesis to be tested is *H1b*: $a_i^{US} = a_i^{EU} = 0$ for i = 4, 5, …, 9.

Table 4.5 shows the estimated coefficients, t-statistics in parentheses and the adjusted R2 for equations (4.2) and (4.3). In the case of the U.S. implied volatility indices, we can see that neither the lagged indices nor the $PC_{i,t-1}^{EU}$ are significant. This suggests that there is no U.S/European effect for the U.S. indices and hence, *H1b* cannot be rejected in this case. On the other hand, *H1b* is rejected for each one of the European implied volatility indices. This is because the $PC_{i,t-1}^{US}$ affects systematically all European indices, which implies that there is a U.S. effect in this case. This asymmetric implied spillover effect is in line with the findings of Hamao et al. (1989) who document that the U.S. conditional volatility is transmitted to other markets but the reverse does not hold.

4. The effect of news announcements on implied volatility spillovers

4.1 The announcement and surprise effect of news releases: Definitions

We investigate whether implied volatility spillovers persist even once the effect of news announcements on the dynamics of implied volatility is taken into account. To this end, a VAR(1) model that allows for the vector of constants to be affected by news releases is employed. In particular, the announcement and surprise effects of aggregate, regional and individual releases on implied volatility dynamics are considered. The *announcement effect* accounts only for the timing of the releases. In this case, news announcements are modeled merely as events, i.e. dummy variable(s) are employed. The *surprise effect* takes into account the timing as well as the content of the releases. In this case, news announcements are measured by their unexpected component (i.e. surprise element). More specifically, we use

[29] Note that in equation (4.2) the regressor $PC_{i,t-1}^{US}$ (i.e. the lagged first principal component extracted from applying PCA to the U.S. indices by excluding the *i*-th implied volatility index) has not been included. This is because VIX, VXN, and VXD refer to the U.S. Thus, including $PC_{i,t-1}^{US}$ would capture the 'own-country' effect (i.e. the U.S. effect) which has already been taken into account by including $\Delta IV_{i,t-1}$ in equation (4.2).

the absolute value of the standardized surprise element, $S_{i,t}$, of a release of item i at time t suggested by Balduzzi et al. (2001, see also Jiang et al., 2009). This is defined as follows:

$$S_{i,t} = \frac{A_{i,t} - F_{i,t}}{\sigma_i} \tag{4.4}$$

where $A_{i,t}\left(F_{i,t}\right)$ is the Bloomberg released (forecasted) value for the i-th economic variable between t-1 and t, and σ_i is the standard deviation of the unexpected component (i.e. $A_{i,t} - F_{i,t}$) of the announcements for the i-th economic variable for the whole sample period.

Considering the absolute value of $S_{i,t}$, assumes implicitly that only the magnitude and not the sign of the surprise matters.[30] This is in line with Christiansen and Ranaldo (2007) who argue that large positive and negative surprises should affect volatility identically, since a larger surprise implies greater uncertainty. Furthermore, taking the absolute value of equation (4.4) accommodates the construction of an aggregate surprise measure of all news announcements under consideration. This is because our sample includes different announcement types (e.g., real economic activity releases, inflationary releases etc.) and hence, one cannot aggregate their unexpected component without taking its absolute value. The construction of an aggregate surprise measure is also facilitated by the fact that the unexpected component of news announcements has been standardized [see equation (4.4)]. This is because the standardization of the surprise element eliminates the units of measurement and hence, allows aggregating the unexpected component across news announcement items. Thus, the aggregate absolute surprise component, $\overline{S}_t$, of *all* U.S. and European news announcement that occurs between t-1 and t is defined as:

$$\overline{S}_t = \overline{S}_t^{US} + \overline{S}_t^{EU} \tag{4.5}$$

where $\overline{S}_t^{US} = \sum_{i=1}^{12}\left|S_{i,t}^{US}\right|$ $\left(\overline{S}_t^{EU} = \sum_{j=1}^{8}\left|S_{j,t}^{EU}\right|\right)$ is the aggregate U.S. (European) absolute surprise component of the announcements for *all* of the U.S. (European) economic variables that occur

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[30] Beber and Brandt (2009) have considered positive and negative surprises separately and interpret these as bad and good news, respectively. This interpretation is valid since they consider only inflationary announcements within a single country setting. However, such an exercise is not possible in our case since different news announcement types are considered.

between t-1 and t.

4.2 Aggregate news releases: Announcement and surprise effects

Next, the effect of aggregate releases on implied volatility spillovers is explored once we control for the announcement effect of aggregate releases. Aggregate releases have been used in the past to examine the impact of news announcements on volatility only within a single-country setting (see Nofsinger and Prucyk, 2003, and de Goeij and Marquering, 2006). In a multi-country setting, Albuquerque and Vega (2009) have considered the effect of aggregate surprises on return co-movements rather than volatility though. The following hypothesis is formulated:

H2a: *Implied volatility spillovers do not exist once we account for the announcement effect of aggregate releases.*

This hypothesis is tested by estimating a VAR(1) model that allows for the vector of constants to be affected by aggregate releases:

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + A * D_t + \varepsilon_t \tag{4.6}$$

where $\Delta IV_t = IV_t - IV_{t-1} = \begin{bmatrix} \Delta IV^{US}_{t,\,(3\times1)} \\ \Delta IV^{EU}_{t,\,(6\times1)} \end{bmatrix}$ is a (9x1) vector with $\Delta IV^{US}_t \left[\Delta IV^{EU}_t \right]$ being the (3x1) [(6x1)] vector of changes in the three U.S. (six European) implied volatility indices between t-1 and t, C is a (9x1) vector of constants, Φ and $A = \begin{bmatrix} A_{1,\,(3\times1)} \\ A_{2,\,(6\times1)} \end{bmatrix}$ are matrices of coefficients [(9x9) and (9x1), respectively], $D_t = \begin{bmatrix} D^*_t \\ D^{**}_t \end{bmatrix}$ is a (2x1) binary vector with $D^*_t \left(D^{**}_t \right)$ being a dummy variable that takes the value 1 when the announcement for *any* economic variable occurs between 4:15pm ET (11:30am ET) on day t-1 and 4:15pm ET (11:30am ET) on day t and 0 otherwise, $A * D_t = \begin{bmatrix} A_1 \otimes D^*_t \\ A_2 \otimes D^{**}_t \end{bmatrix}$ is a Khatri-Rao product and ε_t is a (9x1) vector of residuals.

The construction of the aggregate dummy variable is contingent on whether the dependent variable in specification (4.6) is a U.S. or a European volatility index. For example, consider a day t where only one announcement item is released, e.g., the FOMC rate decision is announced at 2:15pm ET (see Figure 4.1). This release might have an impact on $\Delta IV_{i,t}$ for i = 1, 2, 3 (i.e. for the U.S. implied volatility indices) and $\Delta IV_{i,t+1}$ for i = 4, 5, 6, 7, 8, 9 (i.e. for the European implied volatility indices). This is because the U.S. option markets close at 4:15pm ET and the European ones close at 11:30pm ET. Hence, the aggregate dummy variable for the U.S. implied volatility indices takes the value 1 at time t, while for the European ones takes the value 1 at time t+1. Therefore, specification (4.6) is estimated by using the seemingly unrelated regression (SUR) rather than the ordinary least squares (OLS) methodology. This is because, the individual equations in (4.6) do not have identical explanatory variables and hence, there is an efficiency gain by employing SUR instead of OLS (see Zellner, 1962).

So far, the content of the news announcements has been ignored and releases have been considered merely as events. We turn now to consider the content of the news announcement items. To this end, we employ the aggregate absolute surprise component of news announcements [equation (4.5)]. Hence, the following hypothesis is formulated to examine the aggregate surprise effect:

H2b: *Implied volatility spillovers do not exist once we account for the surprise effect of aggregate releases.*

H2b is tested by augmenting a VAR(1) model with the aggregate surprise variable:

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + A * \overline{S}_t + \varepsilon_t \tag{4.7}$$

where $\Delta IV_t = IV_t - IV_{t-1} = \begin{bmatrix} \Delta IV^{US}_{t,\,(3\times1)} \\ \Delta IV^{EU}_{t,\,(6\times1)} \end{bmatrix}$ is a (9x1) vector with $\Delta IV_t^{US}\left[\Delta IV_t^{EU}\right]$ being the (3x1) [(6x1)] vector of changes in the U.S. (European) implied volatility indices between t-1 and t, C is a (9x1) vector of constants, Φ and $A = \begin{bmatrix} A_{1,(3\times1)} \\ A_{2,(6\times1)} \end{bmatrix}$ are matrices of coefficients [(9x9) and (9x1), respectively], $\overline{S}_t = \begin{bmatrix} \overline{S}_t^{*} \\ \overline{S}_t^{**} \end{bmatrix}$ is a (2x1) vector with $\overline{S}_t^{*}\left(\overline{S}_t^{**}\right)$ being the aggregate surprise component of the announcements for *any* economic variable that occur between 4:15pm ET (11:30am ET) on day t-1 and 4:15pm ET (11:30am ET) on day t, $A * \overline{S}_t = \begin{bmatrix} A_1 \otimes \overline{S}_t^{*} \\ A_2 \otimes \overline{S}_t^{**} \end{bmatrix}$ is a Khatri-Rao product and ε_t is a (9x1) vector of residuals.

Tables 4.6 and 4.7 show the results for the VAR(1) model that allows for the vector of constants to be affected by the aggregate dummy [*H2a*, equation (4.6)] and the aggregate surprise variable [*H2b*, equation (4.7)], respectively. The estimated coefficients, the t-statistics and the adjusted R^2 are reported. In Table 4.6 we can see that implied volatility spillovers are still present despite the fact that we have taken into account economic fundamentals as measured by the release of news announcements. This implies the presence of volatility contagion across countries. On another aside, we can see that aggregate releases have an announcement effect on implied volatility dynamics. Interestingly, this is in contrast to the findings pertinent to stock return co-movement where aggregate releases have been found to have an insignificant effect (see Karaolyi and Stulz, 1996). In Table 4.6 we can also see that the coefficients of the aggregate dummy variable is negative in all cases and hence, news announcements reduce implied volatility. This is consistent with the findings of the literature on the effect of news announcements on implied volatility (see e.g., Patell and Wolfson, 1979, Donders and Vorst, 1996, Ederington and Lee, 1996, Fornari and Mele, 2001, Kim and Kim, 2003, Fornari, 2004, Steeley, 2004, Beber and Brandt, 2006, Äijö, 2008) and implied volatility indices within a single-country setting (see e.g., Nikkinen and Sahlström, 2001, 2004a, Chen and Clements, 2007). Interestingly, it is in contrast with the findings on the reaction of volatility measures other than implied volatility to news releases (see e.g., Jones et al., 1998, who document that the conditional volatility in bond markets increases on the announcement day). Similar results are found in the case that the surprise effect of aggregate releases is taken into account. More specifically, in Table 4.7 we can see that volatility contagion exists since implied volatility spillovers continue to show up in the case where the surprise effect of aggregate releases is considered, as well. In addition, the aggregate surprise element of news announcements has a negative effect on implied volatility changes. This is in line with the findings of Fornari (2004) and suggests that larger news announcement surprises result in a higher reduction in implied volatility.

4.3 Regional news releases: Announcement and surprise effects

Next, we make a distinction between U.S. and European news announcement items. In particular, we examine whether implied volatility spillovers are preserved after the effect of *regional* aggregate announcements are taken into account. Previous studies that investigated the impact of both European and U.S. releases on the implied volatility of a specific country have found mixed results (see e.g., Nikkinen and Sahlström, 2004b, and Äijö, 2008). Thus, the following hypothesis is formulated:

H3a: *Implied volatility spillovers do not exist once we account for the announcement effect of the U.S. and European releases.*

H3a is tested by considering the aggregate dummy variables for the U.S. and European news announcements separately in a VAR framework. More specifically, a VAR(1) model that allows for the vector of constants to be affected by regional aggregate dummy variables, is estimated by using the SUR methodology:

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + A * D_t^{US} + B * D_t^{EU} + \varepsilon_t \qquad (4.8)$$

where $A = \begin{bmatrix} A_{1,(3\times1)} \\ A_{2,(6\times1)} \end{bmatrix}$ and $B = \begin{bmatrix} B_{1,(3\times1)} \\ B_{2,(6\times1)} \end{bmatrix}$ are (9x1) matrices of coefficients, $D_t^r = \begin{bmatrix} D_t^{r,*} \\ D_t^{r,**} \end{bmatrix}$ is a (2x1) binary vector for the news announcements of region r (r = 1, 2 for U.S. and Europe, respectively) with $D_t^{r,*}$ $\left(D_t^{r,**}\right)$ being a dummy variable that takes the value 1 when the announcement for any economic variable of region r occurs between 4:15pm ET (11:30am ET) on day t-1 and 4:15pm ET (11:30am ET) on day t and 0 otherwise, $A * D_t^{US} = \begin{bmatrix} A_1 \otimes D_t^{US,*} \\ A_1 \otimes D_t^{US,**} \end{bmatrix}$ and $B * D_t^{US} = \begin{bmatrix} B_1 \otimes D_t^{EU,*} \\ B_1 \otimes D_t^{EU,**} \end{bmatrix}$ are Khatri-Rao products and ε_t is a (9x1) vector of residuals.

We also examine whether implied volatility spillovers are preserved once the content of regional news announcements has been taken into account. Thus, the following hypothesis is formulated:

H3b: *Implied volatility spillovers do not exist once we account for the surprise effect of the*

U.S. and European releases.

H3b is tested by considering a VAR(1) model that allows for the vector of constants to be affected by regional aggregate surprise variables:

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + A * \overline{S}_t^{US} + B * \overline{S}_t^{EU} + \varepsilon_t \tag{4.9}$$

where $A = \begin{bmatrix} A_{1,(3\times1)} \\ A_{2,(6\times1)} \end{bmatrix}$ and $B = \begin{bmatrix} B_{1,(3\times1)} \\ B_{2,(6\times1)} \end{bmatrix}$ are (9x1) matrices of coefficients, $\overline{S}_t^r = \begin{bmatrix} \overline{S}_t^{r,*} \\ \overline{S}_t^{r,**} \end{bmatrix}$ is a (2x1)

is a (2x1) vector with $\overline{S}_t^{r,*}\left(\overline{S}_t^{r,**}\right)$ being the aggregate surprise component of the announcements for *any* economic variables of region *r* (*r* = 1, 2 for U.S. and Europe, respectively) that occur between 4:15pm ET (11:30am ET) on day *t*-1 and 4:15pm ET (11:30am ET) on day *t*, $A * \overline{S}_t^{US} = \begin{bmatrix} A_1 \otimes \overline{S}_t^{US,*} \\ A_1 \otimes \overline{S}_t^{US,**} \end{bmatrix}$ and $B * \overline{S}_t^{US} = \begin{bmatrix} B_1 \otimes \overline{S}_t^{EU,*} \\ B_1 \otimes \overline{S}_t^{EU,**} \end{bmatrix}$ are Khatri-Rao products and ε_t is a (9x1) vector of residuals. Equation (4.9) is estimated by using the SUR methodology.

Tables 4.8 and 4.9 show the results for the VAR(1) model that allows for the vector of constants to be affected by the regional dummy [*H3a*, equation (4.8)] and the regional surprise variables [*H3b*, equation (4.9)], respectively. In the case that the regional announcement effect is taken into account, we can see in Table 4.8 that *H3a* is rejected, i.e. implied volatility spillovers continue driving the dynamics of implied volatilities . In addition, only the regional U.S. news announcements are found to exert a significant impact on most implied volatility indices. This implies that the systematic announcement effect that was found for the aggregate releases (Table 4.6) stems from the U.S. news announcements. This is in line with the findings of Nikkinen and Sahström (2004b) who found that only the U.S. news announcements affect implied volatility within a single-country setting. In the case that the regional surprise effect of news announcements is taken into account, we can see in Table 4.9 that *H3b* is rejected. This suggests that volatility contagion effects exist. Furthermore, the U.S. (European) surprise element is significant for most U.S. and European (only European) implied volatility indices. The fact that the European releases are found to be significant only in the case where they are modeled as surprises and not as events, is in accordance with the market efficiency hypothesis. It implies that the content of the European news announcements needs to be taken into account for the purposes of explaining the dynamics of implied volatility.

4.4 Individual news releases: Announcement and surprise effects

So far, we have investigated whether implied volatility spillovers drive the dynamics of implied volatilities after taking into account the announcement and surprise effect of aggregate releases, as well as that of the regional ones. Next, we turn our attention to the effect of individual news announcements on the presence of implied volatility spillovers as a driver of volatility dynamics. In the case that the announcement effect of individual releases is considered, the following hypothesis is tested:

H4a: *Implied volatility spillovers do not exist once we account for the announcement effect of the individual releases.*

To test this hypothesis, the impact of scheduled news announcements on the nine implied volatility indices is incorporated in the VAR model and the following specification is estimated by using the SUR methodology:

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + A \odot D_t^{US} + B \odot D_t^{EU} + \varepsilon_t \tag{4.10}$$

where $A = \begin{bmatrix} A_{1,(3\times12)} \\ A_{2,(6\times12)} \end{bmatrix}$ and $B = \begin{bmatrix} B_{1,(3\times8)} \\ B_{2,(6\times8)} \end{bmatrix}$ are matrices of coefficients [(9x12) and (9x8), respectively], $D_t^{US} = \begin{bmatrix} D_t^{US,*} \\ D_t^{US,**} \end{bmatrix}$ is a (9x12) binary matrix for the twelve individual U.S. news announcements with $D_t^{US,*}$ $\left[D_t^{US,**}\right]$ being a (3x12) [(6x12)] binary matrix the (*i*,*j*)-th element of which is a dummy variable that takes the value 1 when an announcement for the *j*-th individual U.S. economic variable occurs between 4:15pm ET (11:30am ET) on day *t*-1 and 4:15pm ET (11:30am ET) on day *t* and 0 otherwise, $D_t^{EU} = \begin{bmatrix} D_t^{EU,*} \\ D_t^{EU,**} \end{bmatrix}$ is a (9x8) binary matrix for the eight individual European news announcements with $D_t^{EU,*}$ $\left[D_t^{EU,**}\right]$ being a (3x8) [(6x8)] binary matrix the (*i*,*j*)-th element of which is a dummy variable that takes the value 1 when an announcement for the *j*-th individual European economic variable occurs between 4:15pm ET (11:30am ET) on day *t*-1 and 4:15pm ET (11:30am ET) on day *t* and 0 otherwise, $A \odot D_t^{US}$ and $B \odot D_t^{EU}$ are Hadamard products and ε_t is a (9x1) vector of residuals.

We also examine whether implied volatility spillovers persist after the surprise effect of individual news announcements is taken into account. Hence, *H4b* is formulated:

H4b: *Implied volatility spillovers do not exist once we account for the surprise effect of the individual releases.*

$$\Delta IV_t = C + \Phi \Delta IV_{t-1} + A \odot \overline{S}_t^{US} + B \odot \overline{S}_t^{EU} + \varepsilon_t \tag{4.11}$$

where $A = \begin{bmatrix} A_{1,(3\times12)} \\ A_{2,(6\times12)} \end{bmatrix}$ and $B = \begin{bmatrix} B_{1,(3\times8)} \\ B_{2,(6\times8)} \end{bmatrix}$ are matrices of coefficients [(9x12) and (9x8), respectively], $\overline{S}_t^{US} = \begin{bmatrix} \overline{S}_t^{US,*} \\ \overline{S}_t^{US,**} \end{bmatrix}$ is a (9x12) matrix of the surprise component of the individual U.S. news announcements with $\overline{S}_t^{US,*}$ $\left[\overline{S}_t^{US,**}\right]$ being a (3x12) [(6x12)] matrix of the surprise component of the individual U.S. announcements that occur between 4:15pm ET (11:30am ET) on day *t*-1 and 4:15pm ET (11:30am ET) on day *t*, $\overline{S}_t^{EU} = \begin{bmatrix} \overline{S}_t^{EU,*} \\ \overline{S}_t^{EU,**} \end{bmatrix}$ is a (9x8) matrix of the surprise component of the individual European news announcements with $\overline{S}_t^{EU,*}$ $\left[\overline{S}_t^{EU,**}\right]$ being a (3x8) [(6x8)] matrix of the surprise component of the individual European announcements that occur between 4:15pm ET (11:30am ET) on day *t*-1 and 4:15pm ET (11:30am ET) on day *t*, $A \odot \overline{S}_t^{US}$ and $B \odot \overline{S}_t^{EU}$ are Hadamard products and ε_t is a (9x1) vector of residuals.

Tables 4.10 and 4.11 show the results for the VAR(1) model augmented by the dummy [*H4a*, equation (4.10)] and surprise variables [*H4b*, equation (4.11)] for the individual news announcement items, respectively. In Table 4.10 we can see that volatility contagion is present since implied volatility spillovers are preserved just as was the case with the announcement effect of aggregate releases. Furthermore, individual news announcement items do not affect the dynamics of implied volatility indices. The only exception occurs for the U.S. GDP releases that have an impact on most volatility indices and for the U.S. FOMC announcements that affect only the U.S. indices. Similar findings are obtained in the case where the content of news announcements is considered. More specifically, in Table 4.11 we can see that volatility spillovers persist and the unexpected component of individual news announcements does not affect the dynamics of implied volatility indices either. The only exception occurs for the U.S. CCI and the FOMC that affect the U.S. implied volatility indices and the EU-CCI that affects the European ones. These results are in line with the findings for the regional releases where European releases were found to be significant only when their content is considered (see Section 4.3).

Interestingly, the fact that the U.S. CCI and EU-CCI releases are found to be significant in the case where they are modeled as surprises rather than events, is in accordance with the market efficiency theory. Furthermore, this implies that the content of these two news announcement items needs to be taken into account for the purposes of explaining the dynamics of implied volatility. Similarly, the finding that FOMC releases affect implied volatility dynamics, irrespectively of whether these are measured as dummy or surprise variables, is also in line with the market efficiency theory. On the other hand, the fact that the U.S. GDP news announcements affect significantly most volatility indices when they are considered merely as events rather than surprises is not consistent with the market efficiency hypothesis. This is because this results implies that the dynamics of implied volatility are affected by the expected (i.e. timing) and not the unexpected (i.e. surprise) component of the U.S. GDP releases.

5. The effect of news announcements on the magnitude of implied volatility spillovers

In this section, we investigate whether news announcements affect the magnitude of implied volatility spillovers.[31] This question has been addressed within an asset return spillover framework (Canto and Kräussl, 2006, Connolly and Wang, 1998), but has not been explored

[31] The magnitude of implied volatility spillovers might also depend on other variables that measure the degree of integration of the countries under consideration. This is similar to the return co-movement case where return correlations have been found to increase with external trade (Chen and Zhang, 1997). We do not investigate this as trade data are not available at a daily frequency.

by the literature in an implied volatility setting. To this end, the announcement and surprise effect of aggregate and regional releases is explored by employing a VAR(1) model that allows for the matrix of coefficients of the autoregressive terms to be affected by the news announcements.

5.1 Aggregate news releases: Announcement and surprise effects

First, we examine whether the magnitude of implied volatility spillovers is the same on announcement and non-announcement dates when aggregate news announcements are considered. Thus, the following hypothesis is tested:

H5a: *Aggregate releases do not have an announcement effect on the magnitude of implied volatility spillovers.*

To test this hypothesis, the following specification is estimated by using the SUR methodology:

$$\Delta IV_t = C + \left(A + B * D_t\right)\Delta IV_{t-1} + \varepsilon_t \qquad (4.12)$$

where C is a (9x1) vector of constants, A and $B = \begin{bmatrix} B_{1,(3\times 9)} \\ B_{2,(6\times 9)} \end{bmatrix}$ are (9x9) matrices of coefficients, $D_t = \begin{bmatrix} D_t^{*} \\ D_t^{**} \end{bmatrix}$ is a (2x1) binary vector with $D_t^{*}\left(D_t^{**}\right)$ being a dummy variable that takes the value 1 when the announcement for *any* economic variable occurs between 4:15pm ET (11:30am ET) on day t-1 and 4:15pm ET (11:30am ET) on day t and 0 otherwise, $B * D_t = \begin{bmatrix} B_1 \otimes D_t^{*} \\ B_2 \otimes D_t^{**} \end{bmatrix}$ is a Khatri-Rao product and ε_t is a (9x1) vector of residuals. Note that equation (4.12) allows for the matrix of the coefficients of the autoregressive terms to be affected by the aggregate news announcements within a VAR modeling framework (see for a similar approach e.g., Connolly and Wang, 1998, Canto and Kräussl, 2006, who examine the impact of news announcements within a return spillover framework).

Next, we examine whether the magnitude of implied volatility spillovers is the same on announcement and non-announcement days when the *content* of aggregate news announcements is considered. The impact of the surprise element of aggregate news announcements on the magnitude of implied volatility spillovers is also investigated. To this end, the following hypothesis is considered:

H5b: *Aggregate releases do not have a surprise effect on the magnitude of implied volatility spillovers.*

To test this hypothesis, the matrix of the coefficients of the autoregressive terms is allowed to be affected by the aggregate surprise component of news announcements within a VAR modeling framework. Hence, the following specification is estimated by using the SUR methodology:

$$\Delta IV_t = C + \left(A + B * \overline{S}\right)\Delta IV_{t-1} + \varepsilon_t \qquad (4.13)$$

where C is a (9x1) vector of constants, A and $B = \begin{bmatrix} B_{1,(3\times 9)} \\ B_{2,(6\times 9)} \end{bmatrix}$ are (9x9) matrices of coefficients, $\overline{S}_t = \begin{bmatrix} \overline{S}_t^{*} \\ \overline{S}_t^{**} \end{bmatrix}$ is a (2x1) vector with $S_t^{*}\left(S_t^{**}\right)$ being the aggregate surprise component of the announcements for *any* economic variable that occur between 4:15pm ET (11:30am ET) on day *t*-1 and 4:15pm ET (11:30am ET) on day *t*, $B * \overline{S}_t = \begin{bmatrix} B_1 \otimes \overline{S}_t^{*} \\ B_2 \otimes \overline{S}_t^{**} \end{bmatrix}$ is a Khatri-Rao product and ε_t is a (9x1) vector of residuals.

Tables 4.12 and 4.13 show the results for the announcement [*H5a*, equation (4.12)] and surprise effect [*H5b*, equation (4.13)] of releases on the magnitude of implied volatility spillovers, respectively. In Table 4.12 we can see that the announcement effect of aggregate releases is weak, since aggregate news announcements do not affect the magnitude of implied volatility spillovers in most cases. The only exception occurs for VBEL, VSMI and VSTOXX. In particular, aggregate releases affect the magnitude of the impact of VBEL to all European implied volatility indices, and the impact of VSMI and VSTOXX to most U.S. and European volatility indices. In Table 4.13 we can see that the surprise effect of aggregate releases is stronger than their respective announcement effect. This is because the surprise element of aggregate news announcements has an impact on the magnitude of implied volatility spillovers in many cases. In particular, we can see that aggregate releases affect the impact of VIX, VXD, VCAC and VSMI on most volatility indices, that of VDAX and VBEL on all U.S. indices, and that of VSTOXX on most European ones. These findings suggest that the content of news announcements (and not their occurrence) needs to be considered for the purposes of examining the magnitude of volatility spillovers.

5.2 Regional news releases: Announcement and surprise effects

Next, we distinguish between releases of U.S. and European economic variables and investigate whether the magnitude of implied volatility spillovers is the same on announcement and non-announcement days when regional news announcements are considered:

H6a: *The U.S. and European releases do not have an announcement effect on the magnitude of implied volatility spillovers.*

H6a is tested by considering a VAR modeling framework where the matrix of coefficients of the autoregressive terms is allowed to be affected by the regional aggregate news announcements. Hence, the following specification is estimated by using the SUR methodology:

$$\Delta IV_t = C + \left(A + B * D^{US} + \Gamma * D^{EU}\right)\Delta IV_{t-1} + \varepsilon_t \tag{4.14}$$

where C is a (9x1) vector of constants, A, $B = \begin{bmatrix} B_{1,(3\times 9)} \\ B_{2,(6\times 9)} \end{bmatrix}$ and $\Gamma = \begin{bmatrix} \Gamma_{1,(3\times 9)} \\ \Gamma_{2,(6\times 9)} \end{bmatrix}$ are (9x9) matrices of coefficients, $D_t^r = \begin{bmatrix} D_t^{r,*} \\ D_t^{r,**} \end{bmatrix}$ is a (2x1) vector for the news announcements of region r (r = 1,2 for U.S. and Europe, respectively) with $D_t^{r,*}\left(D_t^{r,**}\right)$ being a dummy variable that takes the value 1 when the announcement for any economic variable of region r occurs between 4:15pm ET (11:30am ET) on day t-1 and 4:15pm ET (11:30am ET) on day t and 0 otherwise, $B * D^{US} = \begin{bmatrix} B_1 \otimes D_t^{US,*} \\ B_2 \otimes D_t^{US,**} \end{bmatrix}$ and $\Gamma * D^{EU} = \begin{bmatrix} \Gamma_1 \otimes D_t^{EU,*} \\ \Gamma_2 \otimes D_t^{EU,**} \end{bmatrix}$ are Khatri-Rao products, and ε_t is a (9x1) vector of residuals.

Next, we study whether the magnitude of implied volatility spillovers is the same on announcement and non-announcement days when the *content* of regional releases is considered. To this end the following hypothesis is formulated:

H6b: *The U.S. and European releases do not have a surprise effect on the magnitude of implied volatility spillovers.*

H6b is tested by allowing the matrix of the coefficients of the autoregressive terms to be affected by the regional aggregate surprise component of news announcements within a VAR setting. In other words, the following specification is estimated by using the SUR methodology:

$$\Delta IV_{1,t} = c_1 + \Delta IV_t = C + \left(A + B * \overline{S}^{US} + \Gamma * \overline{S}^{EU} \right) \Delta IV_{t-1} + \varepsilon_t \qquad (4.15)$$

where C is a (9x1) vector of constants, A, $B = \begin{bmatrix} B_{1,(3\times9)} \\ B_{2,(6\times9)} \end{bmatrix}$ and $\Gamma = \begin{bmatrix} \Gamma_{1,(3\times9)} \\ \Gamma_{2,(6\times9)} \end{bmatrix}$ are (9x9) matrices of coefficients, $\overline{S}_t^r = \begin{bmatrix} \overline{S}_t^* \\ \overline{S}_t^{**} \end{bmatrix}$ is a (2x1) vector for the news announcements of region r (r = 1, 2 for U.S. and Europe, respectively) with $\overline{S}_t^* \left(\overline{S}_t^{**} \right)$ being the aggregate surprise component of the announcements for *any* economic variable of region r that occur between 4:15pm ET (11:30am ET) on day t-1 and 4:15pm ET (11:30am ET) on day t, $B * \overline{S}^{US} = \begin{bmatrix} B_1 \otimes \overline{S}_t^{US'} \\ B_2 \otimes \overline{S}_t^{US'} \end{bmatrix}$ and $\Gamma * \overline{S}^{EU} = \begin{bmatrix} \Gamma_1 \otimes \overline{S}_t^{EU'} \\ \Gamma_2 \otimes \overline{S}_t^{EU'} \end{bmatrix}$ are Khatri-Rao products, and ε_t is a (9x1) vector of residuals.

Tables 4.14 and 4.15 show the results for the announcement [*H6a*, equation (4.14)] and surprise effect [*H6b*, equation (4.15)] of releases on the magnitude of implied volatility spillovers, respectively. In Table 4.14 we can see that the announcement effect of regional releases is weak, since regional news announcements do not affect the magnitude of implied volatility spillovers in most cases. The only exception occurs for VSMI and VSTOXX where the transmission of VSMI and VSTOXX to the U.S. (other European) markets is affected by the U.S. and European aggregate releases (only European releases). In Table 4.15 we can see that the surprise effect of regional news announcements shows up more evidently when their content is considered. More specifically, the results for VSMI and VSTOXX are similar to the findings for the dummy variables specification [*H6a*, equation (4.14), Table 4.14]. Additionally, the surprise element of the European releases affects the magnitude of spillover of VXN, VDAX and VAEX to all U.S. volatility indices. These findings imply that the content of the European news announcements needs to be taken into account when one investigates the magnitude of volatility spillovers.

6. Conclusions

We have investigated for the first time the effect of scheduled U.S. and European news announcements to the international transmission of implied volatility. To this end, an extensive dataset of major European and U.S. implied volatility indices and various news announcements items have been employed. Both the timing (announcement effect) and the content (surprise effect) of the respective releases has been examined within a VAR setting. First, the question whether implied volatility spillovers continue to show up once the effect of aggregate, regional, and individual releases is taken into account has been explored. Next, the impact of aggregate and regional news announcements on the magnitude of implied volatility spillovers has been investigated.

In the case where no-news announcements are considered, we found that there are implied volatility spillovers between and within regions. More specifically, U.S. volatility has been found to drive the European implied volatility indices; the reverse does not hold though. In the case where news announcements are incorporated in the analysis, implied volatility spillovers continue to drive the dynamics of implied volatilities. On another aside, the effect of releases is found to depend on the degree of aggregation of news and the way that these are modeled. In particular, aggregate releases have both a significant announcement and surprise effect. In the case of regional releases, the two effects are significant only for the U.S. news announcements, while only the surprise effect is significant for the European releases. On the other hand, most individual releases do not contain additional information over the documented implied volatility spillovers. Interestingly, in the cases where the aggregate, regional and individual releases have a significant impact this is negative. Finally, regarding the effect of aggregate and regional news announcements on the magnitude of implied volatility spillovers, a weak announcement effect has been documented. In particular, news announcements have been found to be insignificant in most cases when they are modeled as events. On the other hand, their surprise effect shows up more evidently.

The results have at least four main implications. First, volatility contagion is present since the news about economic fundamentals do not account entirely for the implied volatility interrelations. Second, the fact that aggregate and regional releases have a significant surprise effect to both the dynamics of implied volatility and the magnitude of implied volatility spillovers is consistent with the market efficiency hypothesis for option markets. Third, the impact of releases within an implied volatility spillover setting becomes more evident as the level of aggregation of news announcements increases consecutively from individual to regional and aggregate releases. Fourth, the occurrence of scheduled releases decreases uncertainty once we account for volatility spillovers. This is consistent with the findings of the previous literature on the effect of news announcements to implied volatility within a single-country setting and suggests that potentially profitable volatility option trading strategies may be devised.

	VIX	VXN	VXD	VDAX	VCAC	VAEX	VBEL	VSMI	VSTOXX
	Panel A: Summary statistics for the levels of the implied volatility indices								
# Observations	2,246	2,246	2,246	2,271	2,280	2,282	2,283	2,256	2,271
Mean	21.95	30.45	20.61	26.35	24.45	26.13	20.26	21.19	25.99
Std. Deviation	10.40	14.09	9.65	11.79	10.75	12.64	9.09	10.06	11.82
Skewness	1.84	0.94	1.71	1.37	1.42	1.33	1.45	1.67	1.35
Kurtosis	7.81	2.92	7.12	4.72	5.18	4.39	5.86	6.56	4.73
Jarque-Bera	**3,434***	**331***	**2,689***	**986***	**1,218***	**858***	**1,583***	**2,246***	**975***
ρ_1	**0.96***	**0.96***	**0.96***	**0.98***	**0.98***	**0.98***	**0.97***	**0.98***	**0.98***
ADF	-2.28	**-3.79****	-3.38	-2.69	-3.36	-3.26	-2.84	-3.14	-2.81
	Panel B: Summary statistics for the daily changes in the implied volatility indices								
# Observations	2,165	2,164	2,165	2,237	2,245	2,249	2,251	2,210	2,237
Mean	-0.03	-0.06	-0.03	-0.01	0.00	0.00	0.00	-0.01	-0.01
Std. Deviation	1.73	1.64	1.49	1.71	1.93	1.71	1.61	1.36	1.92
Skewness	0.18	0.01	0.42	1.44	1.06	0.97	0.49	0.45	1.90
Kurtosis	23.56	13.85	20.13	25.07	39.90	12.81	29.00	32.21	29.80
Jarque-Bera	**38,151***	**10,611***	**26,530***	**46,153***	**127,784***	**9,374***	**63,488***	**78,664***	**68,294***
ρ_1	**-0.096***	-0.030	**-0.088***	0.039	**-0.098***	-0.005	**-0.157***	**0.127***	-0.032
ADF	**-18.33***	**-35.51***	**-37.13***	**-23.44***	**-37.00***	**-47.30***	**-32.03***	**-32.87***	**-23.22***

Table 4.1: 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 ρ_1, the Jarque-Bera and the Augmented Dickey Fuller (ADF, a trend and an intercept have been included in the test equation) 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 from February 2, 2001 to January 8, 2010.

Panel A: US Economic Variables	
Non-Farm Payroll (NFP)	Change in the number of people employed over the last month, not including jobs relating to the farming industry.
Consumer Confidence Index (CCI)	Degree of optimism that consumers feel about the overall state of the economy and their personal financial situation. It is calculated as the average of responses to five questions: current business conditions, expectations for business conditions in six months, current employment conditions, expectations for employment conditions in six months and expectations for the total family income in six months.
Consumer Price Index (CPI)	Change in prices of all goods and services purchased for consumption by urban households over the last month.
Durable Goods Orders (DGO)	Measures the new orders placed with domestic manufacturers for immediate and future delivery of factory hard goods.
FOMC rate announcement (FOMC)	Federal funds target rate (annualized based on a 360 day)
Gross Domestic Product (GDP)	Market value of all final goods and services made within the borders of the U.S.
Initial Jobless Claims (IJC)	Number of people that filed for unemployment benefits over the last week.
ISM non-manufacturing index (ISM)	Includes prices paid for all purchases including import purchases and purchases of food and energy excluding crude oil.
Leading Indicators (LI)	A composite index of ten economic indicators that should lead overall economic activity
New Home Sales (NHS)	Number of newly constructed homes with a committed sale during the month
Producer Price Index (PPI)	Average changes in prices received by U.S. producers of commodities in all stages of processing.
Retail Sales Less Autos (RS)	Total receipts at stores that sell durable and nondurable goods.
Panel B: European Economic Variables	
ECB Rate Announcement (ECB)	ECB's decision to increase, decrease, or maintain interest rates
Euro-zone Consumer Confidence	Arithmetic average of the balances of four questions: the financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and savings, all over the next 12 months.
Euro-zone CPI (EU-CPI)	Euro-zone consumer price index. Euro-zone is treated as a separate entity by Eurostat. The Euro-zone consists of 12 members as of January 1, 2001.
Euro-zone GDP (EU-GDP)	Measure of the total value of goods and services produced by Euro-zone nations.
Euro-zone PPI (EU-PPI)	Average changes in prices received by producers of commodities in all stages of processing within the Euro-zone.
Euro-zone Retail Sales (EU-RS)	Monthly activity in volume of Retail Trade, except of motor vehicles and motorcycles.
IFO Business Climate (IFO-BC)	A survey is conducted monthly, querying German firms on their expectations for the next six months. Firms rate the future outlook as better, same, or worse.
ZEW Survey (ZEW)	A survey is conducted monthly, querying about 350 institutional investors and analysts on their expectations of future economic growth in Germany within the next 6 months. It represents the difference between positive and negative responses in a survey of about

Table 4.2: Definition of scheduled news announcement items. The entries provide a brief definition of the scheduled announcements for the U.S. (Panel A) and the European (Panel B) economic variables under consideration.

	Source of Report	Time of Release	Frequency	Units	N
		Panel A: US Economic Variables			
NFP	Bureau of Labor Statistics	8:30am ET	Monthly	Thousands	108
CCI	Conference Board	From 9:36am to 10:00am ET	Monthly	Base year 1985 (=100)	107
CPI	Bureau of Labor Statistics	8:30am ET	Monthly	Percentage (%)	107
DGO	U.S. Census Bureau	From 8:30am to 10:00am ET	Monthly	Percentage (%)	107
FOMC	Federal Reserve	From 7:00am to 2:15pm ET(1)	Fed meets 8 times per year	Percentage (%)	74
GDP	Bureau of Economic Analysis	8:30am ET	Monthly	Percentage (%)	74
IJC	Department of Labor	8:30am ET(2)	Weekly	Thousands	107
ISM	Institute for Supply Management	From 8:55am to10:00am ET	Monthly	Percentage (%)	466
LI	Conference Board	From 9:50am to10:00am ET	Monthly	Percentage (%)	85
NHS	U.S. Census Bureau	10:00am ET	Monthly	Thousands	107
PPI	Bureau of Labor Statistics	8:30am ET	Monthly	Percentage (%)	107
RS	U.S. Census Bureau	8:30am ET	Monthly	Percentage (%)	106
		Panel B: European Economic Variables			
ECB	European Central Bank	From 6:44am to 7:45am ET	ECB meets 11 times per year	Percentage (%)	112
EU-CCI	European Commission	From 4:00am to 6:00am ET	Monthly	Value	101
EU-CPI	Eurostat	From 5:00am to 6:00am ET	Monthly	Percentage (%)	106
EU-GDP	Eurostat	From 5:00am to 6:00am ET	Monthly	Percentage (%)	105
EU-PPI	Eurostat	From 4:00am to 6:00am ET	Monthly	Percentage (%)	106
EU-RS	Eurostat	From 5:00am to 6:00am ET	Monthly	Percentage (%) Base year 2005	106
IFO-BC	IFO Institute	From 3:55am to 5:00am ET	Monthly	Base year 2000	106
ZEW	Center for European Economic Research	From 5:00am to 10:00am ET	Monthly	Value	101

(1) Most announcements occur around 2:15pm ET. However, there are some exceptions: 4/18/2001 (10:55am ET), 1/22/2008 (8:30am ET) and 10/8/2008 (7:00am ET).
(2) Most announcements occur at 8:30am ET. However, there is one exception: 12/28/2001 (10:30pm ET).

Table 4.3: Summary of scheduled news announcements. The entries summarize the scheduled announcements for the U.S. (Panel A) and the European (Panel B) economic variables under consideration. The source, the timing, the frequency, the units of measurement and the total number (N) of the news announcements in our sample are reported. The U.S. stock index option markets close at 4:15pm Eastern Time (ET) and the European stock index option markets close at 11:30 am ET. The sample spans the period from February 2, 2001 to January 8, 2010.

	ΔVIX$_t$	ΔVXN$_t$	ΔVXD$_t$	ΔVDAX$_t$	ΔVCAC$_t$	ΔVAEX$_t$	ΔVBEL$_t$	ΔVSMI$_t$	ΔVSTOX$_t$
	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*
C	-0.027	-0.069	-0.022	-0.034	-0.019	-0.032	-0.001	-0.018	-0.034
	(-0.700)	*(-1.892)*	*(-0.661)*	*(-0.951)*	*(-0.479)*	*(-0.892)*	*(-0.040)*	*(-0.649)*	*(-0.861)*
ΔVIX$_{t-1}$	-0.094	-0.058	**0.151****	**0.400***	**0.354***	**0.264***	-0.018	0.069	**0.487***
	(-1.360)	*(-0.869)*	*(2.526)*	*(6.112)*	*(4.804)*	*(3.986)*	*(-0.280)*	*(1.408)*	*(6.828)*
ΔVXN$_{t-1}$	**0.139***	0.042	**0.101****	-0.002	**0.136***	**0.136***	**0.112***	-0.027	**0.093****
	(3.025)	*(0.950)*	*(2.541)*	*(-0.055)*	*(2.788)*	*(3.082)*	*(2.704)*	*(-0.821)*	*(1.972)*
ΔVXD$_{t-1}$	-0.129	-0.019	**-0.342***	-0.059	**-0.223***	-0.097	**0.182***	**0.222***	-0.143
	(-1.647)	*(-0.254)*	*(-5.089)*	*(-0.807)*	*(-2.691)*	*(-1.298)*	*(2.578)*	*(3.999)*	*(-1.781)*
ΔVDAX$_{t-1}$	**0.345***	**0.312***	**0.279***	**-0.119****	0.064	**0.193***	-0.081	**0.249***	**0.162***
	(6.725)	*(6.325)*	*(6.322)*	*(-2.450)*	*(1.164)*	*(3.920)*	*(-1.746)*	*(6.832)*	*(3.064)*
ΔVCAC$_{t-1}$	**-0.123***	**-0.120***	**-0.118***	-0.022	**-0.348***	**-0.116***	**-0.089***	0.024	**-0.055****
	(-4.618)	*(-4.693)*	*(-5.150)*	*(-0.885)*	*(-12.350)*	*(-4.565)*	*(-3.722)*	*(1.262)*	*(-2.031)*
ΔVAEX$_{t-1}$	-0.046	0.034	-0.046	**-0.152***	-0.014	**-0.224***	**-0.096***	**-0.196***	-0.065
	(-1.173)	*(0.896)*	*(-1.350)*	*(-4.072)*	*(-0.334)*	*(-5.934)*	*(-2.704)*	*(-6.997)*	*(-1.615)*
ΔVBEL$_{t-1}$	0.032	0.036	0.009	**0.064****	**-0.067****	0.042	**-0.240***	**0.121***	**0.078***
	(1.181)	*(1.356)*	*(0.371)*	*(2.475)*	*(-2.321)*	*(1.606)*	*(-9.718)*	*(6.257)*	*(2.805)*
ΔVSMI$_{t-1}$	**-0.281***	**-0.266***	**-0.257***	**-0.121***	**-0.131***	-0.045	-0.051	**-0.202***	**-0.234***
	(-6.341)	*(-6.244)*	*(-6.740)*	*(-2.904)*	*(-2.784)*	*(-1.060)*	*(-1.267)*	*(-6.420)*	*(-5.143)*
ΔVSTOXX$_{t-1}$	-0.052	-0.090	0.011	**0.176***	**0.339***	0.021	**0.342***	**0.079****	**-0.182***
	(-1.098)	*(-1.969)*	*(0.268)*	*(3.906)*	*(6.697)*	*(0.455)*	*(7.956)*	*(2.343)*	*(-3.713)*
Adj. R-squared	**0.054**	**0.037**	**0.062**	**0.122**	**0.172**	**0.102**	**0.152**	**0.220**	**0.148**

Table 4.4: Implied volatility spillovers across markets. The entries report results from the following VAR(1) model: $\Delta IV_t = C + \Phi\Delta IV_{t-1} + \varepsilon$, where $\Delta IV_t = IV_t - IV_{t-1}$ is the (9x1) vector of changes in the implied volatility indices between t-1 and t, *C* is a (9x1) vector of constants, *Φ* is a (9x9) matrix of coefficients and ε is a (9x1) 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 European implied volatility indices have been used. The estimated coefficients, *t*-statistics in parentheses and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The model has been estimated for the period February 2, 2001 to January 1, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(t-stat.)	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*
C	-0.029	-0.065	-0.025	-0.031	-0.024	-0.031	-0.012	-0.017	-0.032
	(-0.861)	*(-1.954)*	*(-0.850)*	*(-1.005)*	*(-0.754)*	*(-0.889)*	*(-0.416)*	*(-0.704)*	*(-0.931)*
ΔIV_{t-1}	-0.062	-0.001	-0.058	-0.063	**-0.344***	-0.206	**-0.292***	**-0.197***	-0.156
	(-1.606)	*(-0.024)*	*(-1.420)*	*(-0.676)*	*(-5.565)*	*(-1.846)*	*(-4.613)*	*(-3.342)*	*(-0.886)*
PC_{t-1}^{US}	-	-	-	**0.369***	**0.335***	**0.328***	**0.277***	**0.234***	**0.469***
	-	-	-	*(5.917)*	*(3.450)*	*(7.964)*	*(6.593)*	*(6.570)*	*(4.729)*
PC_{t-1}^{EU}	-0.060	-0.051	-0.045	-0.077	**0.204****	0.055	0.069	**0.215***	-0.096
	(-1.437)	*(-1.112)*	*(-1.113)*	*(-1.001)*	*(2.332)*	*(0.538)*	*(1.216)*	*(3.160)*	*(-0.620)*
Adj. R^2	**0.012**	**0.003**	**0.010**	**0.094**	**0.131**	**0.082**	**0.121**	**0.165**	**0.115**

Table 4.5: The U.S. versus the European effect in implied volatility spillovers. The entries report results from the following regression model for the U.S. implied volatility indices: $\Delta IV_{i,t} = c_i + \varphi_i \Delta IV_{i,t-1} + \alpha_i^{EU} PC_{i,t-1}^{EU} + \varepsilon_{i,t}$, where $\Delta IV_{i,t} = IV_{i,t} - IV_{i,t-1}$ is the change in the i-th implied volatility index between t-1 and t (i = 1 for VIX, 2 for VXN, 3 for VXD) and $PC_{i,t-1}^{EU}$ is the lagged first principal component extracted from applying principal component analysis (PCA) to the set of all European implied volatility indices. The entries also report results from the following regression model for the European implied volatility indices: $\Delta IV_{i,t} = c_i + \varphi_i \Delta IV_{i,t-1} + \alpha_i^{US} PC_{i,t-1}^{US} + \alpha_i^{EU} PC_{i,t-1}^{EU} + \varepsilon_{i,t}$, where i = 4 (for VDAX), 5 (for VCAC), 6 (for VAEX), 7 (for VBEL), 8 (for VSMI), 9 (for VSTOXX) and $PC_{i,t-1}^{r}$ is the lagged first principal component extracted from applying PCA to the set of implied volatility indices of region r (r = 1 for the U.S. and r = 2 for European indices) where the i-th implied volatility index is excluded from this set. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients, t-statistics in parentheses and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(t-stat.)	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*
C	**0.127****	**0.126****	**0.143***	**0.148****	**0.170****	**0.253***	0.098	**0.142***	**0.227***
	(2.006)	*(2.111)*	*(2.634)*	*(2.479)*	*(2.502)*	*(4.167)*	*(1.718)*	*(3.106)*	*(3.441)*
ΔVIX_{t-1}	-0.076	-0.047	**0.160***	**0.424***	**0.354***	**0.285***	-0.029	0.079	**0.518***
	(-1.060)	*(-0.705)*	*(2.599)*	*(6.203)*	*(4.626)*	*(4.123)*	*(-0.459)*	*(1.529)*	*(6.864)*
ΔVXN_{t-1}	**0.130***	0.010	**0.089****	0.000	**0.162***	**0.162***	**0.115***	-0.022	0.099
	(2.598)	*(0.209)*	*(2.054)*	*(-0.008)*	*(3.013)*	*(3.348)*	*(2.572)*	*(-0.619)*	*(1.881)*
ΔVXD_{t-1}	-0.130	0.002	**-0.331***	-0.071	**-0.214****	-0.119	**0.206***	**0.223***	-0.163
	(-1.627)	*(0.028)*	*(-4.798)*	*(-0.923)*	*(-2.489)*	*(-1.537)*	*(2.873)*	*(3.826)*	*(-1.924)*
$\Delta VDAX_{t-1}$	**0.370***	**0.324***	**0.305***	**-0.105****	0.084	**0.202***	**-0.103****	**0.260***	**0.170***
	(6.962)	*(6.497)*	*(6.673)*	*(-2.056)*	*(1.474)*	*(3.917)*	*(-2.168)*	*(6.746)*	*(3.011)*
$\Delta VCAC_{t-1}$	**-0.125***	**-0.122***	**-0.123***	-0.022	**-0.346***	**-0.116***	**-0.082***	0.020	**-0.061****
	(-4.681)	*(-4.874)*	*(-5.338)*	*(-0.874)*	*(-12.152)*	*(-4.501)*	*(-3.441)*	*(1.014)*	*(-2.183)*
$\Delta VAEX_{t-1}$	-0.042	0.040	-0.037	**-0.160***	-0.022	**-0.230***	**-0.117***	**-0.203***	-0.074
	(-1.052)	*(1.059)*	*(-1.092)*	*(-4.183)*	*(-0.507)*	*(-5.930)*	*(-3.288)*	*(-6.996)*	*(-1.744)*
$\Delta VBEL_{t-1}$	0.024	0.024	-0.002	**0.062****	**-0.091***	0.033	**-0.233***	**0.124***	**0.079***
	(0.841)	*(0.914)*	*(-0.084)*	*(2.293)*	*(-2.985)*	*(1.211)*	*(-9.196)*	*(6.009)*	*(2.626)*
$\Delta VSMI_{t-1}$	**-0.270***	**-0.250***	**-0.251***	**-0.105****	**-0.131***	-0.032	-0.041	**-0.190***	**-0.211***
	(-6.042)	*(-5.948)*	*(-6.514)*	*(-2.450)*	*(-2.715)*	*(-0.742)*	*(-1.034)*	*(-5.840)*	*(-4.422)*
$\Delta VSTOXX_{t-1}$	-0.081	**-0.113****	-0.016	**0.156***	**0.314***	0.001	**0.350***	0.065	**-0.199***
	(-1.665)	*(-2.453)*	*(-0.392)*	*(3.325)*	*(5.973)*	*(0.026)*	*(8.008)*	*(1.842)*	*(-3.829)*
D_t	**-0.217***	**-0.273***	**-0.243***	**-0.256***	**-0.269***	**-0.410***	**-0.147****	**-0.233***	**-0.368***
	(-2.779)	*(-3.692)*	*(-3.606)*	*(-3.439)*	*(-3.182)*	*(-5.434)*	*(-2.083)*	*(-4.085)*	*(-4.492)*
Adj. R^2	**0.058**	**0.044**	**0.068**	**0.123**	**0.174**	**0.111**	**0.150**	**0.220**	**0.146**

Table 4.6: Announcement effect of aggregate releases on implied volatility spillovers. The entries report results from a VAR(1) model augmented by the aggregate dummy variable for all the news announcements under consideration [equation (4.6)]. D_t is the aggregate dummy variable of all releases. Equation (4.6) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients, *t*-statistics in parentheses and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(t-stat.)	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*
C	0.084	0.048	0.077	0.048	0.082	**0.110****	0.062	**0.071****	0.085
	(1.788)	*(1.081)*	*(1.886)*	*(1.077)*	*(1.624)*	*(2.445)*	*(1.478)*	*(2.078)*	*(1.733)*
ΔVIX_{t-1}	-0.057	-0.029	**0.170***	**0.461***	**0.387***	**0.337***	-0.039	0.098	**0.572***
	(-0.793)	*(-0.426)*	*(2.727)*	*(6.735)*	*(5.028)*	*(4.890)*	*(-0.601)*	*(1.883)*	*(7.566)*
ΔVXN_{t-1}	**0.127****	0.010	**0.089****	-0.006	**0.156***	**0.152***	**0.115****	-0.022	0.091
	(2.530)	*(0.213)*	*(2.051)*	*(-0.118)*	*(2.911)*	*(3.165)*	*(2.566)*	*(-0.614)*	*(1.735)*
ΔVXD_{t-1}	-0.152	-0.024	**-0.345***	-0.116	**-0.259***	**-0.182****	**0.217***	**0.196***	**-0.227***
	(-1.882)	*(-0.317)*	*(-4.955)*	*(-1.513)*	*(-2.996)*	*(-2.362)*	*(3.004)*	*(3.361)*	*(-2.679)*
$\Delta VDAX_{t-1}$	**0.373***	**0.327***	**0.304***	-0.100	0.083	**0.210***	**-0.112****	**0.259***	**0.181***
	(6.965)	*(6.528)*	*(6.583)*	*(-1.949)*	*(1.438)*	*(4.075)*	*(-2.342)*	*(6.674)*	*(3.215)*
$\Delta VCAC_{t-1}$	**-0.130***	**-0.128***	**-0.126***	-0.028	**-0.354***	**-0.126***	**-0.079***	0.017	**-0.069****
	(-4.879)	*(-5.127)*	*(-5.455)*	*(-1.092)*	*(-12.465)*	*(-4.972)*	*(-3.313)*	*(0.861)*	*(-2.461)*
$\Delta VAEX_{t-1}$	-0.034	0.047	-0.031	**-0.148***	-0.013	**-0.219***	**-0.111***	**-0.196***	-0.060
	(-0.866)	*(1.260)*	*(-0.912)*	*(-3.882)*	*(-0.294)*	*(-5.716)*	*(-3.097)*	*(-6.780)*	*(-1.431)*
$\Delta VBEL_{t-1}$	0.023	0.024	-0.003	**0.062****	**-0.089***	0.037	**-0.236***	**0.123***	**0.082***
	(0.805)	*(0.902)*	*(-0.112)*	*(2.290)*	*(-2.931)*	*(1.366)*	*(-9.268)*	*(6.002)*	*(2.749)*
$\Delta VSMI_{t-1}$	**-0.261***	**-0.242***	**-0.243***	**-0.099****	**-0.122****	-0.024	-0.033	**-0.181***	**-0.204***
	(-5.839)	*(-5.768)*	*(-6.291)*	*(-2.314)*	*(-2.536)*	*(-0.560)*	*(-0.832)*	*(-5.562)*	*(-4.310)*
$\Delta VSTOXX_{t-1}$	-0.085	**-0.114***	-0.018	**0.150***	**0.320***	-0.001	**0.350***	0.065	**-0.210***
	(-1.727)	*(-2.477)*	*(-0.424)*	*(3.197)*	*(6.054)*	*(-0.026)*	*(7.931)*	*(1.817)*	*(-4.054)*
$\bar{S}_t$	**-0.132***	**-0.129***	**-0.119***	**-0.082****	**-0.116***	**-0.164***	**-0.081****	**-0.101***	**-0.125***
	(-3.596)	*(-3.729)*	*(-3.765)*	*(-2.320)*	*(-2.900)*	*(-4.610)*	*(-2.421)*	*(-3.743)*	*(-3.211)*
Adj. R^2	**0.061**	**0.046**	**0.070**	**0.123**	**0.179**	**0.112**	**0.151**	**0.221**	**0.147**

Table 4.7: Surprise effect of aggregate releases on implied volatility spillovers. The entries report results from a VAR(1) model augmented by the aggregate surprise variable for all the news announcements under consideration [equation (4.7)]. $\bar{S}_t$ is the aggregate surprise variable of all releases. Equation (4.7) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients, *t*-statistics in parentheses and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX	ΔVXN	ΔVXD	ΔVDAX	ΔVCAC	ΔVAEX	ΔVBEL	ΔVSMI	ΔVSTOXX
	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*	Coeff. *(t-stat.)*
C	0.078	0.075	0.091	0.119**	0.109	0.190*	0.057	0.114*	0.160*
	(1.333)	(1.353)	(1.812)	(2.146	(1.730	(3.373)	(1.094)	(2.691)	(2.626)
ΔVIX_{t-1}	-0.072	-0.043	0.164*	0.427*	0.352*	0.289*	-0.032	0.082	0.521*
	(-1.002)	(-0.645)	(2.658)	(6.248	(4.588	(4.181)	(-0.495)	(1.575)	(6.888)
ΔVXN_{t-1}	0.125**	0.006	0.085**	-0.002	0.168*	0.160*	0.119*	-0.023	0.099
	(2.496)	(0.124)	(1.960)	(-0.037	(3.113	(3.298)	(2.657)	(-0.635)	(1.869)
ΔVXD_{t-1}	-0.130	0.002	-0.331*	-0.072	-0.218**	-0.122	0.204*	0.221*	-0.166
	(-1.618)	(0.031)	(-4.795)	(-0.944	(-2.526	(-1.564)	(2.845)	(3.799)	(-1.948)
$\Delta VDAX_{t-1}$	0.372*	0.326*	0.307*	-0.105**	0.078	0.201*	-0.107**	0.260*	0.168*
	(7.000)	(6.525)	(6.701)	(-2.064	(1.363	(3.889)	(-2.258)	(6.720)	(2.965)
$\Delta VCAC_{t-1}$	-0.124*	-0.122*	-0.122*	-0.022	-0.346*	-0.115*	-0.081*	0.020	-0.060**
	(-4.658)	(-4.849)	(-5.313)	(-0.857)	(-12.125)	(-4.464)	(-3.423)	(1.035)	(-2.149)
$\Delta VAEX_{t-1}$	-0.044	0.038	-0.039	-0.161*	-0.018	-0.231*	-0.115*	-0.203*	-0.074
	(-1.106)	(1.014)	(-1.140)	(-4.192)	(-0.414)	(-5.937)	(-3.206)	(-6.993)	(-1.737)
$\Delta VBEL_{t-1}$	0.024	0.024	-0.002	0.062**	-0.091*	0.033	-0.233*	0.123*	0.079*
	(0.830)	(0.896)	(-0.099)	(2.280)	(-3.001)	(1.198)	(-9.206)	(5.993)	(2.611)
$\Delta VSMI_{t-1}$	-0.273*	-0.252*	-0.253*	-0.106**	-0.130*	-0.034	-0.041	-0.191*	-0.211*
	(-6.109)	(-6.017)	(-6.585)	(-2.468)	(-2.700)	(-0.776)	(-1.020)	(-5.856)	(-4.439)
$\Delta VSTOXX_{t-1}$	-0.080	-0.111**	-0.015	0.157*	0.316*	0.003	0.351*	0.066	-0.197*
	(-1.631)	(-2.415)	(-0.349)	(3.339)	(6.007)	(0.059)	(8.038)	(1.860)	(-3.790)
D_t^{US}	-0.218*	-0.261*	-0.227*	-0.217*	-0.082	-0.325*	-0.021	-0.189*	-0.256*
	(-2.891)	(-3.664)	(-3.503)	(-3.037)	(-1.007)	(-4.456)	(-0.308)	(-3.433)	(-3.245)
D_t^{EU}	0.074	0.042	0.049	-0.068	-0.210**	-0.099	-0.133	-0.072	-0.115
	(0.888)	(0.542)	(0.680)	(-0.858)	(-2.362)	(-1.231)	(-1.791)	(-1.197)	(-1.307)
Adj. R^2	**0.059**	**0.045**	**0.069**	**0.123**	**0.172**	**0.109**	**0.149**	**0.219**	**0.144**

Table 4.8: Announcement effect of regional releases (i.e. releases of U.S. and European economic variables separately) on implied volatility spillovers. The entries report results from a VAR(1) model augmented by the aggregate dummy variable for the U.S. and European news announcements, separately [equation (4.8)]. $D_t^{US}\left(D_t^{EU}\right)$ is the regional aggregate dummy variable of the U.S. (European) releases. Equation (4.8) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients, *t*-statistics in parentheses and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(t-stat.)	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*	*(t-stat.)*
C	0.087	0.050	0.079	0.046	0.076	**0.107****	0.058	**0.069****	0.083
	(1.844)	*(1.126)*	*(1.943)*	*(1.031)*	*(1.512)*	*(2.383)*	*(1.367)*	*(2.039)*	*(1.694)*
ΔVIX_{t-1}	-0.054	-0.027	**0.172***	**0.459***	**0.381***	**0.334***	-0.044	0.097	**0.570***
	(-0.753)	*(-0.394)*	*(2.767)*	*(6.700)*	*(4.945)*	*(4.845)*	*(-0.689)*	*(1.856)*	*(7.537)*
ΔVXN_{t-1}	**0.127****	0.009	**0.088****	-0.005	**0.159***	**0.153***	**0.117***	-0.022	0.092
	(2.516)	*(0.200)*	*(2.036)*	*(-0.104)*	*(2.955)*	*(3.186)*	*(2.608)*	*(-0.603)*	*(1.746)*
ΔVXD_{t-1}	-0.153	-0.025	**-0.346***	-0.114	**-0.254***	**-0.180****	**0.221***	**0.197***	**-0.225***
	(-1.901)	*(-0.332)*	*(-4.975)*	*(-1.490)*	*(-2.942)*	*(-2.331)*	*(3.064)*	*(3.380)*	*(-2.659)*
$\Delta VDAX_{t-1}$	**0.375***	**0.329***	**0.306***	**-0.101****	0.077	**0.207***	**-0.117****	**0.258***	**0.180***
	(7.007)	*(6.560)*	*(6.626)*	*(-1.985)*	*(1.340)*	*(4.023)*	*(-2.442)*	*(6.640)*	*(3.184)*
$\Delta VCAC_{t-1}$	**-0.131***	**-0.129***	**-0.126***	-0.027	**-0.354***	**-0.126***	**-0.078***	0.017	**-0.068****
	(-4.895)	*(-5.141)*	*(-5.472)*	*(-1.085)*	*(-12.454)*	*(-4.964)*	*(-3.287)*	*(0.866)*	*(-2.457)*
$\Delta VAEX_{t-1}$	-0.036	0.046	-0.033	**-0.146***	-0.008	**-0.217***	**-0.107***	**-0.195***	-0.058
	(-0.901)	*(1.231)*	*(-0.949)*	*(-3.827)*	*(-0.182)*	*(-5.644)*	*(-2.991)*	*(-6.729)*	*(-1.384)*
$\Delta VBEL_{t-1}$	0.023	0.024	-0.003	**0.062****	**-0.090***	0.037	**-0.237***	**0.123***	**0.082***
	(0.810)	*(0.906)*	*(-0.106)*	*(2.278)*	*(-2.965)*	*(1.350)*	*(-9.310)*	*(5.992)*	*(2.739)*
$\Delta VSMI_{t-1}$	**-0.262***	**-0.242***	**-0.243***	**-0.099****	**-0.121****	-0.024	-0.033	**-0.181***	**-0.204***
	(-5.850)	*(-5.776)*	*(-6.303)*	*(-2.312)*	*(-2.527)*	*(-0.556)*	*(-0.820)*	*(-5.562)*	*(-4.310)*
$\Delta VSTOXX_{t-1}$	-0.086	**-0.115****	-0.019	**0.150***	**0.321***	-0.001	**0.351***	0.065	**-0.210***
	(-1.751)	*(-2.496)*	*(-0.448)*	*(3.201)*	*(6.089)*	*(-0.019)*	*(7.969)*	*(1.819)*	*(-4.054)*
$\overline{S}_t^{US}$	**-0.158***	**-0.148***	**-0.143***	-0.056	-0.046	**-0.130***	-0.024	**-0.085****	**-0.101****
	(-3.485)	*(-3.462)*	*(-3.641)*	*(-1.291)*	*(-0.931)*	*(-2.948)*	*(-0.577)*	*(-2.525)*	*(-2.101)*
$\overline{S}_t^{EU}$	-0.084	-0.094	-0.077	**-0.132****	**-0.249***	**-0.231***	**-0.190***	**-0.133***	**-0.172****
	(-1.274)	*(-1.513)*	*(-1.342)*	*(-2.082)*	*(-3.505)*	*(-3.610)*	*(-3.196)*	*(-2.764)*	*(-2.456)*
Adj. R^2	**0.061**	**0.046**	**0.070**	**0.123**	**0.181**	**0.113**	**0.153**	**0.221**	**0.147**

Table 4.9: Surprise effect of regional releases (i.e. releases of U.S. and European economic variables separately) on implied volatility spillovers. The entries report results from a VAR(1) model augmented by the aggregate surprise variable for the U.S. and European news announcements, separately [equation (4.9)]. $\overline{S}_t^{US}\left(\overline{S}_t^{EU}\right)$ is the regional aggregate surprise variable of the U.S. (European) releases. Equation (4.9) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients, *t*-statistics in parentheses and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
C	0.085	0.071	0.090	**0.111****	**0.132****	**0.172***	0.078	**0.101****	**0.150****
ΔVIX_{t-1}	-0.097	-0.063	**0.143****	**0.415***	**0.327***	**0.276***	-0.038	0.066	**0.505***
ΔVXN_{t-1}	**0.142***	0.016	**0.096****	0.002	**0.171***	**0.168***	**0.123***	-0.013	**0.107****
ΔVXD_{t-1}	-0.116	0.015	**-0.318***	-0.062	**-0.192****	-0.113	**0.213***	**0.230***	-0.152
$\Delta VDAX_{t-1}$	**0.375***	**0.326***	**0.308***	**-0.104****	0.089	**0.199***	**-0.106****	**0.263***	**0.173***
$\Delta VCAC_{t-1}$	**-0.120***	**-0.119***	**-0.119***	-0.022	**-0.348***	**-0.112***	**-0.081***	0.021	**-0.059****
$\Delta VAEX_{t-1}$	-0.040	0.038	-0.036	**-0.163***	-0.017	**-0.230***	**-0.114***	**-0.204***	-0.072
$\Delta VBEL_{t-1}$	0.021	0.020	-0.005	**0.060****	**-0.097***	0.030	**-0.235***	**0.120***	**0.075****
$\Delta VSMI_{t-1}$	**-0.269***	**-0.243***	**-0.249***	**-0.109****	**-0.134***	-0.039	-0.039	**-0.189***	**-0.217***
$\Delta VSTOXX_{t-1}$	-0.085	**-0.113****	-0.017	**0.158***	**0.314***	0.009	**0.349***	0.064	**-0.199***
D_t^{NFP}	-0.336	**-0.429***	-0.292	**-0.452****	-0.360	**-0.583***	-0.127	**-0.311****	**-0.503****
D_t^{CCI}	-0.316	-0.217	-0.236	0.116	0.291	0.049	-0.118	-0.117	-0.122
D_t^{CPI}	-0.296	-0.353	-0.278	-0.168	-0.059	**-0.506***	0.014	-0.200	-0.156
D_t^{DGO}	-0.270	-0.281	-0.211	-0.311	-0.445	-0.224	0.130	**-0.360****	-0.343
D_t^{FOMC}	**-0.435****	**-0.367****	**-0.414***	-0.184	-0.096	0.015	-0.008	-0.068	-0.092
D_t^{GDP}	**-0.403****	**-0.385****	-0.289	**-0.438****	**-0.480****	**-0.451****	**-0.472***	**-0.360***	**-0.412****
D_t^{IJC}	-0.103	-0.108	-0.143	-0.094	-0.160	**-0.320***	-0.025	-0.031	-0.159
D_t^{ISM}	0.081	0.063	0.044	-0.055	-0.179	-0.049	0.073	-0.070	-0.156
D_t^{LI}	-0.121	-0.179	-0.116	-0.101	0.177	0.097	-0.087	-0.067	-0.212
D_t^{NHS}	0.025	0.109	0.054	-0.066	0.333	-0.149	-0.077	0.044	-0.040
D_t^{PPI}	-0.233	-0.336	-0.252	-0.171	-0.092	-0.105	-0.119	-0.046	-0.125
D_t^{RS}	0.175	0.118	0.136	0.085	0.049	0.059	0.254	-0.043	0.215
D_t^{ECB}	0.339	0.335	0.340	0.366	0.413	**0.515***	0.234	0.266	**0.433****
D_t^{EU-CCI}	0.224	0.321	0.146	-0.136	-0.321	-0.199	-0.316	-0.114	-0.225
D_t^{EU-CPI}	0.326	0.025	0.179	-0.049	-0.133	0.106	0.017	0.076	0.068
D_t^{EU-GDP}	-0.091	-0.013	0.031	-0.245	-0.073	-0.153	-0.145	-0.255	-0.312
D_t^{EU-PPI}	0.116	0.076	0.100	-0.023	-0.182	-0.103	0.002	-0.002	-0.136
D_t^{EU-RS}	-0.121	-0.194	-0.179	-0.251	-0.263	-0.226	-0.268	-0.261	-0.241
D_t^{IFO}	0.006	-0.055	-0.038	-0.033	-0.066	-0.128	-0.060	-0.010	0.006
D_t^{ZEW}	-0.309	-0.308	-0.307	-0.152	**-0.662***	**-0.377****	**-0.352****	-0.265	-0.340
Adj. R^2	**0.062**	**0.048**	**0.071**	**0.123**	**0.177**	**0.112**	**0.152**	**0.220**	**0.144**

Table 4.10: Announcement effect of the individual news announcement items on implied volatility spillovers. The entries report results from a VAR(1) model augmented by dummy variables for the individual news announcement items under consideration [equation (4.10)]. Equation (4.10) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX$_t$	ΔVXN$_t$	ΔVXD$_t$	ΔVDAX$_t$	ΔVCAC$_t$	ΔVAEX$_t$	ΔVBEL$_t$	ΔVSMI$_t$	ΔVSTOXX$_t$
C	0.094**	0.050	0.086**	0.046	0.089	0.119*	0.068	0.074**	0.095
ΔVIX$_{t-1}$	-0.061	-0.033	0.167*	0.455*	0.364*	0.329*	-0.046	0.095	0.568*
ΔVXN$_{t-1}$	0.144*	0.024	0.102**	-0.009	0.158*	0.158*	0.127*	-0.021	0.094
ΔVXD$_{t-1}$	-0.148	-0.021	-0.341*	-0.102	-0.228*	-0.167**	0.232*	0.203*	-0.209**
ΔVDAX$_{t-1}$	0.367*	0.318*	0.298*	-0.107**	0.078	0.205*	-0.121**	0.255*	0.178*
ΔVCAC$_{t-1}$	-0.124*	-0.123*	-0.120*	-0.025	-0.352*	-0.122*	-0.075*	0.019	-0.064**
ΔVAEX$_{t-1}$	-0.039	0.041	-0.036	-0.141*	-0.004	-0.217*	-0.113*	-0.195*	-0.057
ΔVBEL$_{t-1}$	0.020	0.022	-0.005	0.062**	-0.092*	0.036	-0.238*	0.122*	0.081*
ΔVSMI$_{t-1}$	-0.249*	-0.231*	-0.232*	-0.111**	-0.118**	-0.029	-0.026	-0.179*	-0.209*
ΔVSTOXX$_{t-1}$	-0.091	-0.114**	-0.022	0.155*	0.314*	0.000	0.345*	0.063	-0.216*
$\bar{S}_t^{NFP}$	-0.247	-0.312	-0.231	-0.191	-0.174	-0.346**	-0.086	-0.161	-0.240
$\bar{S}_t^{CCI}$	-0.693*	-0.594*	-0.583*	0.482**	0.275	0.065	-0.474**	-0.020	0.044
$\bar{S}_t^{CPI}$	-0.295	-0.336	-0.280	-0.073	0.020	-0.374**	-0.038	-0.251	-0.171
$\bar{S}_t^{DGO}$	-0.253	-0.214	-0.223	-0.189	-0.320	-0.364**	0.013	-0.269**	-0.313
$\bar{S}_t^{FOMC}$	-0.586*	-0.645*	-0.534*	0.093	-0.186	0.297	0.203	-0.066	0.231
$\bar{S}_t^{GDP}$	-0.106	-0.103	-0.108	-0.116	-0.172	-0.315	-0.280	-0.217	-0.199
$\bar{S}_t^{IJC}$	-0.079	-0.066	-0.076	-0.100	-0.047	-0.178**	0.005	-0.050	-0.146
$\bar{S}_t^{ISM}$	0.133	0.180	0.126	0.028	-0.010	0.011	0.135	-0.088	0.013
$\bar{S}_t^{LI}$	-0.274	-0.252	-0.258	-0.168	-0.029	-0.127	-0.246	-0.155	-0.341
$\bar{S}_t^{NHS}$	0.024	0.075	0.053	0.042	0.236	0.098	0.137	0.099	0.088
$\bar{S}_t^{PPI}$	-0.323	-0.334**	-0.280	-0.198	-0.118	-0.174	-0.204	-0.042	-0.155
$\bar{S}_t^{RS}$	0.257	0.299	0.212	0.295	0.054	0.277	0.407**	0.141	0.394**
$\bar{S}_t^{ECB}$	0.137	-0.165	0.115	0.169	0.360	0.086	-0.132	0.091	0.363
$\bar{S}_t^{EU-CCI}$	-0.300	-0.192	-0.264	-0.355**	-0.735*	-0.344**	-0.613*	-0.285**	-0.477**
$\bar{S}_t^{EU-CPI}$	0.256	0.201	0.197	-0.043	-0.224	-0.142	0.119	-0.095	0.012
$\bar{S}_t^{EU-GDP}$	-0.038	-0.035	-0.014	-0.238	-0.009	-0.276	-0.215	-0.161	-0.258
$\bar{S}_t^{EU-PPI}$	-0.050	-0.043	-0.031	-0.059	-0.027	-0.279	-0.063	-0.051	-0.233
$\bar{S}_t^{EU-RS}$	-0.221	-0.217	-0.230	-0.260	-0.311	-0.233	-0.320	-0.202	-0.340
$\bar{S}_t^{IFO}$	-0.105	-0.108	-0.091	-0.232	-0.250	-0.290	0.025	-0.153	-0.136
$\bar{S}_t^{ZEW}$	-0.367	-0.297	-0.316	-0.048	-0.695*	-0.336	-0.325	-0.191	-0.263
Adj. R^2	0.069	0.055	0.078	0.123	0.185	0.112	0.160	0.219	0.148

Table 4.11: Surprise effect of the individual news announcement items on implied volatility spillovers. The entries report results from a VAR(1) model augmented by absolute surprise variables for the individual news announcement items under consideration. Results have been obtained by using the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
C	-0.003	-0.043	-0.006	-0.005	0.007	-0.004	0.010	-0.001	0.002
ΔVIX_{t-1}	0.088	-0.004	**0.216****	**0.537***	0.217	0.214	0.119	**0.305***	**0.636***
ΔVXN_{t-1}	**0.172****	0.049	**0.149****	-0.045	0.176	0.045	0.092	-0.027	0.062
ΔVXD_{t-1}	**-0.325****	-0.091	**-0.401***	-0.177	-0.063	0.058	0.125	-0.115	-0.268
$\Delta VDAX_{t-1}$	**0.321***	**0.249***	**0.257***	-0.075	0.081	0.116	-0.060	**0.161****	0.169
$\Delta VCAC_{t-1}$	**-0.116***	**-0.130***	**-0.115***	**-0.115***	**-0.504***	**-0.087****	**-0.077****	-0.053	-0.056
$\Delta VAEX_{t-1}$	0.012	**0.122****	0.020	-0.049	0.010	**-0.251***	**-0.205***	**-0.185***	0.088
$\Delta VBEL_{t-1}$	0.032	0.004	-0.029	**0.163***	0.082	**0.117****	**-0.111***	**0.142***	**0.208***
$\Delta VSMI_{t-1}$	-0.028	-0.045	**-0.131****	**0.166****	0.084	**0.317***	0.103	**0.160***	0.133
$\Delta VSTOXX_{t-1}$	**-0.293***	**-0.256***	-0.103	-0.104	0.135	**-0.159****	**0.211***	0.040	**-0.630***
D_t*ΔVIX_{t-1}	-0.254	-0.065	-0.083	-0.197	0.184	0.103	-0.242	**-0.320***	-0.230
D_t *ΔVXN_{t-1}	-0.082	-0.060	-0.086	0.068	-0.026	0.169	0.004	0.032	0.023
D_t *ΔVXD_{t-1}	0.304	0.125	0.092	0.190	-0.201	-0.270	0.172	**0.475***	0.226
D_t *$\Delta VDAX_{t-1}$	0.059	0.109	0.064	-0.077	-0.010	0.134	-0.089	0.109	-0.024
D_t *$\Delta VCAC_{t-1}$	-0.045	-0.006	-0.026	**0.182***	**0.298***	-0.046	-0.007	**0.146***	-0.016
D_t *$\Delta VAEX_{t-1}$	-0.086	-0.137	-0.086	**-0.183****	-0.068	0.088	**0.171****	0.024	**-0.272***
D_t *$\Delta VBEL_{t-1}$	-0.021	0.025	0.033	**-0.206***	**-0.314***	**-0.150***	**-0.211***	**-0.093****	**-0.220***
D_t *$\Delta VSMI_{t-1}$	**-0.338***	**-0.279***	**-0.174****	**-0.387***	**-0.305***	**-0.586***	**-0.256***	**-0.546***	**-0.484***
D_t *$\Delta VSTOXX_{t-1}$	**0.363***	**0.243****	0.154	**0.379***	**0.240****	**0.201****	**0.209****	-0.026	**0.702***
Adj. R^2	**0.066**	**0.045**	**0.065**	**0.144**	**0.192**	**0.124**	**0.164**	**0.252**	**0.178**

Table 4.12: Announcement effect of the aggregate releases for all the economic variables on the magnitude of implied volatility spillovers. The entries report results from a VAR(1) model that allows for the matrix of coefficients of the autoregressive terms to be affected by the aggregate dummy of the news announcements for all the economic variables [equation (4.12)]. D_t is the aggregate dummy variable of all releases. Equation (4.12) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
C	-0.007	-0.043	-0.007	0.002	0.008	0.000	0.012	0.006	0.010
ΔVIX_{t-1}	**0.262***	**0.256***	**0.418***	**0.633***	**0.538***	**0.388***	0.155	**0.310***	**0.749***
ΔVXN_{t-1}	0.073	-0.043	0.036	0.009	**0.158****	**0.179***	0.089	-0.013	0.073
ΔVXD_{t-1}	**-0.389***	**-0.227****	**-0.500***	**-0.279***	**-0.411***	**-0.223****	0.056	-0.044	**-0.364***
$\Delta VDAX_{t-1}$	**0.212***	**0.210***	**0.165***	-0.075	0.009	0.112	**-0.180***	**0.115****	0.133
$\Delta VCAC_{t-1}$	**-0.081****	**-0.103***	**-0.084***	-0.042	**-0.431***	**-0.095***	-0.047	-0.001	-0.020
$\Delta VAEX_{t-1}$	0.054	0.084	0.025	-0.018	0.073	**-0.147***	**-0.108****	**-0.136***	0.085
$\Delta VBEL_{t-1}$	-0.040	-0.040	**-0.061****	**0.082****	**-0.127***	0.030	**-0.187***	**0.119***	**0.104***
$\Delta VSMI_{t-1}$	-0.083	-0.086	**-0.110****	0.012	0.068	**0.154***	**0.110****	0.043	-0.022
$\Delta VSTOXX_{t-1}$	**-0.153****	**-0.143****	-0.035	-0.065	**0.227***	-0.111	**0.245***	0.032	**-0.490***
$\bar{S}_t * \Delta VIX_{t-1}$	**-0.387***	**-0.335***	**-0.299***	**-0.212***	**-0.156****	-0.045	**-0.235***	**-0.251***	**-0.216***
$\bar{S}_t * \Delta VXN_{t-1}$	0.058	0.063	0.066	-0.041	0.003	-0.042	0.007	-0.009	-0.016
$\bar{S}_t * \Delta VXD_{t-1}$	**0.295***	**0.243***	**0.188***	**0.229***	0.153	0.039	**0.215***	**0.288***	**0.191****
$\bar{S}_t * \Delta VDAX_{t-1}$	**0.167***	**0.125***	**0.150***	-0.031	0.074	**0.096****	0.078	**0.144***	0.043
$\bar{S}_t * \Delta VCAC_{t-1}$	**-0.094***	**-0.057****	**-0.076***	0.004	**0.086***	**-0.058****	**-0.048****	0.016	**-0.091***
$\bar{S}_t * \Delta VAEX_{t-1}$	**-0.114***	-0.047	**-0.069****	**-0.167***	**-0.116***	-0.070	0.011	-0.048	**-0.184***
$\bar{S}_t * \Delta VBEL_{t-1}$	**0.083****	**0.077****	**0.074***	-0.040	0.026	-0.002	**-0.082***	-0.029	-0.025
$\bar{S}_t * \Delta VSMI_{t-1}$	**-0.135***	**-0.130***	**-0.114***	-0.055	**-0.116***	**-0.168***	**-0.131***	**-0.201***	**-0.115***
$\bar{S}_t * \Delta VSTOXX_{t-1}$	0.090	0.029	0.021	**0.246***	0.088	**0.122****	**0.111****	-0.001	**0.349***
Adj. R^2	**0.091**	**0.064**	**0.095**	**0.148**	**0.191**	**0.120**	**0.171**	**0.252**	**0.184**

Table 4.13: Surprise effect of the aggregate releases for all the economic variables on the magnitude of implied volatility spillovers. The entries report results from a VAR(1) model that allows for the matrix of coefficients of the autoregressive terms to be affected by the aggregate surprise of the news announcements for all the economic variables [equation (4.13)]. Equation (4.13) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
C	-0.007	-0.043	-0.009	-0.010	0.012	-0.005	0.005	-0.006	-0.001
ΔVIX_{t-1}	-0.077	-0.133	0.055	**0.550***	**0.305****	**0.222****	-0.017	**0.180****	**0.633***
ΔVXN_{t-1}	**0.220***	0.132	**0.197***	-0.018	**0.168****	0.078	0.071	0.011	0.112
ΔVXD_{t-1}	-0.199	-0.030	**-0.287***	-0.193	-0.114	0.018	**0.339***	0.011	**-0.304****
$\Delta VDAX_{t-1}$	**0.269***	**0.228***	**0.227***	-0.062	-0.006	0.116	-0.116	**0.195***	0.131
$\Delta VCAC_{t-1}$	**-0.138***	**-0.142***	**-0.121***	**-0.120***	**-0.503***	**-0.086****	-0.045	**-0.053****	**-0.088****
$\Delta VAEX_{t-1}$	0.014	0.097	0.013	-0.102	-0.023	**-0.256***	**-0.220***	**-0.187***	0.050
$\Delta VBEL_{t-1}$	0.030	0.028	-0.014	**0.144***	0.020	**0.097****	**-0.136***	**0.118***	**0.187***
$\Delta VSMI_{t-1}$	**-0.191***	**-0.190***	**-0.248***	0.107	0.001	**0.229***	0.016	**0.107****	0.027
$\Delta VSTOXX_{t-1}$	-0.129	-0.124	0.005	-0.047	**0.294***	-0.099	**0.292***	0.035	**-0.490***
D_t^{US} *ΔVIX_{t-1}	0.000	0.207	0.186	0.177	0.114	0.231	-0.122	**0.229****	-0.095
D_t^{US} *ΔVXN_{t-1}	-0.083	-0.106	-0.112	0.036	-0.043	0.172	0.096	0.028	-0.016
D_t^{US} *ΔVXD_{t-1}	-0.053	-0.224	-0.242	-0.245	-0.245	**-0.461***	-0.162	-0.176	0.076
D_t^{US} *$\Delta VDAX_{t-1}$	0.043	0.072	0.010	**-0.269***	-0.091	0.077	-0.032	-0.139	-0.056
D_t^{US} *$\Delta VCAC_{t-1}$	0.013	-0.012	0.011	**0.182***	**0.339***	-0.027	-0.002	0.074	0.101
D_t^{US} *$\Delta VAEX_{t-1}$	0.015	0.032	0.006	**-0.176****	0.034	0.080	0.096	-0.037	**-0.201****
D_t^{US} *$\Delta VBEL_{t-1}$	0.048	0.074	0.062	**-0.168***	**-0.278***	-0.087	**-0.185***	-0.034	**-0.171***
D_t^{US} *$\Delta VSMI_{t-1}$	**-0.346***	**-0.276***	**-0.241***	**-0.387***	-0.163	**-0.485***	**-0.166****	**-0.606***	**-0.494***
D_t^{US} *$\Delta VSTOXX_{t-1}$	**0.304***	**0.200****	**0.177****	**0.589***	0.148	**0.193****	**0.260***	**0.377***	**0.597***
D_t^{EU} *ΔVIX_{t-1}	0.162	0.050	0.154	**-0.407***	0.040	-0.064	**0.334****	**-0.316***	-0.091
D_t^{EU} *ΔVXN_{t-1}	-0.116	-0.150	-0.120	0.005	0.072	-0.002	-0.123	-0.059	-0.051
D_t^{EU} *ΔVXD_{t-1}	0.057	0.235	0.037	**0.482***	0.001	0.180	-0.199	**0.475***	0.205
D_t^{EU} *$\Delta VDAX_{t-1}$	0.138	0.088	0.140	0.235	**0.506***	0.105	-0.036	**0.358***	0.078
D_t^{EU} *$\Delta VCAC_{t-1}$	-0.010	0.066	-0.032	-0.012	-0.036	-0.090	**-0.149****	0.061	-0.111
D_t^{EU} *$\Delta VAEX_{t-1}$	**-0.197****	**-0.228****	-0.115	0.125	-0.095	0.063	**0.316***	**0.176***	-0.119
D_t^{EU} *$\Delta VBEL_{t-1}$	-0.118	**-0.171***	-0.080	**-0.130****	0.045	-0.116	0.057	-0.088	**-0.146****
D_t^{EU} *$\Delta VSMI_{t-1}$	**0.488***	**0.375***	**0.459***	0.027	-0.156	-0.125	0.049	0.061	**0.259****
D_t^{EU} *$\Delta VSTOXX_{t-1}$	**-0.271****	-0.190	**-0.316***	**-0.279***	-0.236	0.012	**-0.273***	**-0.599***	0.090
Adj. R^2	**0.074**	**0.055**	**0.083**	**0.162**	**0.198**	**0.118**	**0.178**	**0.294**	**0.173**

Table 4.14: Announcement effect of regional announcements (i.e. releases of U.S. and European economic variables separately) on the magnitude of implied volatility spillovers. The entries report results from a VAR(1) model that allows for the matrix of coefficients of the autoregressive terms to be affected by the U.S. and European aggregate dummies of the news announcements for the U.S. and European economic variables, respectively [equation (4.14)]. $D_t^{US}\left(D_t^{EU}\right)$ is the regional aggregate dummy variable of the U.S. (European) releases. Equation (4.14) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

	ΔVIX_t	ΔVXN_t	ΔVXD_t	$\Delta VDAX_t$	$\Delta VCAC_t$	$\Delta VAEX_t$	$\Delta VBEL_t$	$\Delta VSMI_t$	$\Delta VSTOXX_t$
C	0.002	-0.034	0.001	0.002	0.022	0.003	0.012	0.003	0.013
ΔVIX_{t-1}	0.254*	0.244*	0.414*	0.641*	0.531*	0.372*	0.174**	0.318*	0.733*
ΔVXN_{t-1}	0.080	-0.034	0.043	0.004	0.146**	0.181*	0.083	-0.018	0.075
ΔVXD_{t-1}	-0.384*	-0.217**	-0.495*	-0.291*	-0.408*	-0.211**	0.044	-0.062	-0.356*
$\Delta VDAX_{t-1}$	0.201*	0.203*	0.155*	-0.059	0.023	0.117	-0.196*	0.127*	0.134
$\Delta VCAC_{t-1}$	-0.091*	-0.113*	-0.094*	-0.040	-0.424*	-0.095*	-0.051	0.001	-0.021
$\Delta VAEX_{t-1}$	0.055	0.085	0.024	-0.033	0.078	-0.146*	-0.112*	-0.152*	0.085
$\Delta VBEL_{t-1}$	-0.055	-0.056	-0.077**	0.077**	-0.122*	0.022	-0.186*	0.111*	0.095*
$\Delta VSMI_{t-1}$	-0.067	-0.072	-0.096	-0.005	0.038	0.160*	0.110**	0.036	-0.012
$\Delta VSTOXX_{t-1}$	-0.146**	-0.137**	-0.026	-0.053	0.228*	-0.113	0.262*	0.047	-0.488*
$\bar{S}_t^{US} * \Delta VIX_{t-1}$	-0.279*	-0.206**	-0.163	0.137	-0.053	0.076	-0.202**	0.111	-0.010
$\bar{S}_t^{US} * \Delta VXN_{t-1}$	-0.029	-0.037	-0.013	-0.035	-0.048	-0.041	-0.001	0.002	-0.046
$\bar{S}_t^{US} * \Delta VXD_{t-1}$	0.228**	0.152	0.062	-0.121	0.167	-0.079	0.167	-0.063	0.041
$\bar{S}_t^{US} * \Delta VDAX_{t-1}$	0.099	0.064	0.082	-0.199*	-0.091	0.053	0.054	-0.031	-0.026
$\bar{S}_t^{US} * \Delta VCAC_{t-1}$	-0.0887*	-0.055	-0.068**	-0.012	0.092**	-0.079**	-0.028	-0.029	-0.084**
$\bar{S}_t^{US} * \Delta VAEX_{t-1}$	-0.018	0.046	0.023	-0.155*	-0.057	-0.038	0.035	-0.034	-0.131*
$\bar{S}_t^{US} * \Delta VBEL_{t-1}$	0.111*	0.115*	0.107*	-0.053	-0.042	0.023	-0.124*	-0.026	-0.027
$\bar{S}_t^{US} * \Delta VSMI_{t-1}$	-0.312*	-0.290*	-0.283*	-0.115**	-0.142*	-0.243*	-0.207*	-0.320*	-0.257*
$\bar{S}_t^{US} * \Delta VSTOXX_{t-1}$	0.200*	0.124*	0.135*	0.442*	0.177*	0.172*	0.172*	0.228*	0.413*
$\bar{S}_t^{EU} * \Delta VIX_{t-1}$	-0.201	-0.236**	-0.164	-0.391*	-0.105	-0.064	-0.095	-0.350*	-0.275**
$\bar{S}_t^{EU} * \Delta VXN_{t-1}$	0.228*	0.262*	0.217*	0.008	0.199**	-0.026	0.036	0.027	0.070
$\bar{S}_t^{EU} * \Delta VXD_{t-1}$	-0.040	-0.016	-0.047	0.349*	-0.226	0.018	0.083	0.328*	0.097
$\bar{S}_t^{EU} * \Delta VDAX_{t-1}$	0.300*	0.249*	0.265*	0.186**	0.553*	0.134	0.096	0.329*	0.128
$\bar{S}_t^{EU} * \Delta VCAC_{t-1}$	-0.022	0.023	-0.012	-0.043	0.010	-0.015	-0.079	0.023	-0.115**
$\bar{S}_t^{EU} * \Delta VAEX_{t-1}$	-0.263*	-0.203*	-0.185*	-0.021	-0.322*	-0.120	0.061	0.130**	-0.242*
$\bar{S}_t^{EU} * \Delta VBEL_{t-1}$	0.070	0.031	0.056	0.017	0.170*	-0.054	0.056	-0.001	-0.005
$\bar{S}_t^{EU} * \Delta VSMI_{t-1}$	0.180*	0.140**	0.176*	-0.013	-0.100	-0.057	0.029	-0.049	0.095
$\bar{S}_t^{EU} * \Delta VSTOXX_{t-1}$	-0.187*	-0.194**	-0.261*	-0.084	-0.055	0.077	-0.128	-0.421*	0.272*
Adj. R^2	0.116	0.089	0.126	0.172	0.210	0.120	0.182	0.308	0.193

Table 4.15: Surprise effect of regional announcements (i.e. releases of U.S. and European economic variables, separately) on the magnitude of implied volatility spillovers. The entries report results from a VAR(1) model that allows for the matrix of coefficients of the autoregressive terms to be affected by the U.S. and European absolute surprise variables of the news announcements for the U.S. and European economic variables, respectively [equation (4.15)]. $\bar{S}_t^{US}\left(\bar{S}_t^{EU}\right)$ is the regional surprise variable of the U.S. (European) releases. Equation (4.15) has been estimated by the SUR method. Closing prices for the U.S. and European implied volatility indices have been used. The estimated coefficients and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level, respectively. The *t*-statistics have not been reported due to space limitation but are available from the authors upon request. The model has been estimated for the period February 2, 2001 to January 8, 2010.

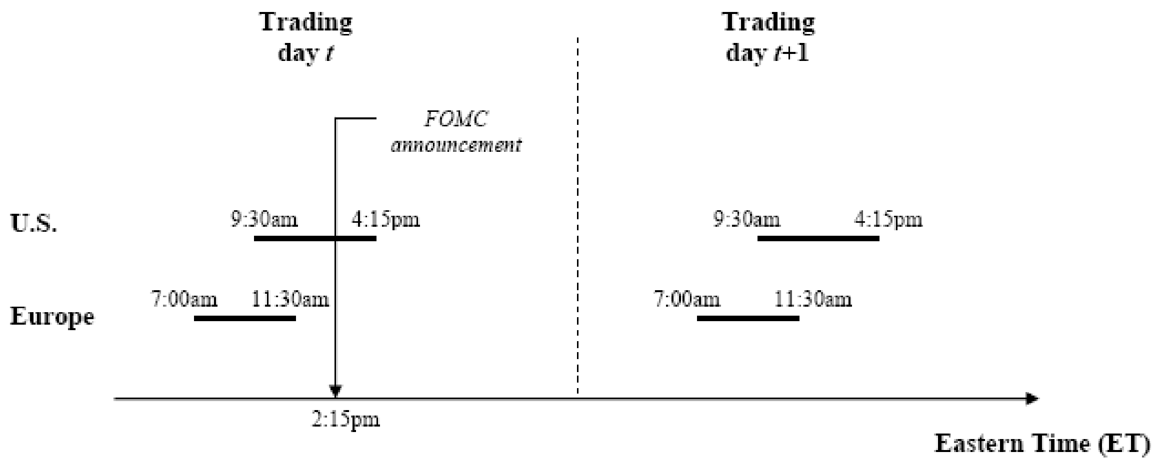

Figure 4.1: Trading hours for the U.S. and European option markets. This figure shows the trading hours for the U.S. and European option markets and the FOMC announcement that is the only announcement that occurs between the close of the European and the close of the U.S. markets; the announcement occurs at 2:15pm ET on day *t*.

Chapter 5: Conclusions

This thesis has studied for the first time the efficiency of volatility derivatives markets. To this end, it has addressed primarily two research questions. First, it has explored whether the recently inaugurated and fast growing volatility futures markets are efficient. To this end, Jensen's (1978) definition of market efficiency has been adopted. Second, it has examined the effect of news announcements on volatility spillovers by considering implied volatility markets.

Regarding the first research question, the efficiency of volatility futures markets was initially studied indirectly by performing trading strategies with VIX and VXD volatility futures that were based on point and interval forecasts of the corresponding *underlying* implied volatility indices (Chapter 2). In this case, implied volatility indices have been found to be statistically predictable. However, this predictability could not be exploited in an economically significant way, since no abnormal profits were be attained by trading volatility futures. This suggests that the market efficiency hypothesis cannot be rejected for the volatility futures markets.

Next, the efficiency of volatility futures markets was examined directly without resorting to the predictability of the underlying implied volatility index (Chapter 3). More specifically, the predictability of VIX futures prices per se was investigated by constructing point and interval forecasts from alternative model specifications. Having evaluated these forecasts under a statistical and economic metric, we documented only a weakly statistically predictable pattern in the evolution of volatility futures prices that cannot be exploited for trading purposes. These findings are in line with those found in Chapter 2 and suggest that the hypothesis that the VIX volatility futures market is informationally efficient cannot be rejected.

With respect to the second research question, the role of news announcements in explaining volatility spillovers was investigated for the first time (Chapter 4). In particular, I have explored whether news announcements account for the transmission of implied volatility across countries and whether releases affect the magnitude of volatility spillovers. Using an extensive dataset of European and U.S. implied volatility indices and scheduled news announcements, both the timing (announcement effect) and the content (surprise effect) of aggregate, regional and individual releases has been examined. Implied volatility spillovers have been found to exist between and within regions. They continued to be present even when releases are incorporated in the analysis. On another aside, the effect of releases has been found to depend on the degree of aggregation of news and the way that these are modeled. With respect to the effect of releases on the magnitude of implied volatility spillovers, news announcements have been found to be insignificant in most cases when they are modeled as events. On the other hand, their surprise effect shows up more evidently. These findings are consistent with the market efficiency hypothesis for option markets

The results of this thesis have at least three contributions. First, the newly inaugurated CBOE volatility futures markets are informational efficient. However, the absence of abnormal profitability in these markets does not invalidate the trading of these contracts. This is because volatility futures can be used for hedging against changes in volatility [see Brenner and Galai (1989, 1993)]. Second, contagion is present in implied volatility markets since the news about economic fundamentals do not account entirely for the implied volatility interrelations. Third, the occurrence of scheduled releases decreases uncertainty within an implied volatility spillover framework. This has implications for the efficiency of volatility derivatives markets, since is suggests that potentially profitable volatility derivatives trading strategies may be devised.

Future research should investigate the efficiency of other volatility derivatives markets, as well [e.g., the recently inaugurated volatility options market in CBOE]. The efficiency of these markets should also be explored under alternative and more complex model specifications, since the answer to the efficiency question is always conditional on the model under consideration [see e.g., Welch and Goyal (2008)]. The issue of predictability in volatility derivatives markets should also be studied at longer horizons. This is because, it has been documented that the predictability in asset returns increases at longer horizons [see e.g., Poterba and Summers (1988)]. Finally, intra-day data should also be considered to test whether any predictable patterns may be detected within the day.

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Appendix A: Construction of implied volatility indices

In 1993, the Chicago Board Options Exchange introduced the first implied volatility index, namely VIX (currently termed VXO) which originally measured the implied volatility of a synthetic at-the-money (ATM) S&P 100 index option with 30 calendar days to maturity. In 2003 the construction algorithm and definition of VIX changed and the *old* VIX index was renamed to VXO [see e.g., Whaley (2000), Carr and Wu (2006), CBOE VIX white paper]. The new VIX tracks the implied volatility of a synthetic S&P 500 index option that has 30 calendar days to maturity. Since then, implied volatility indices that track the implied volatility of a synthetic option that has a constant time-to-maturity have mushroomed in the European and U.S. markets (see Table A.1).

A-1 Construction of the VXO (old VIX) index

In the case of the VXO index, S&P 100 option prices are used to construct the average implied volatility of a synthetic option contract that is near-the-money and matures in 30 calendar days. More specifically, the implied volatilities calibrated by employing the model of Merton (1973) from four pairs of American-style S&P 100 index calls and puts are employed; two nearest maturities and two near-the-money strike prices are considered. Next, implied volatilities are averaged for each pair of options and interpolated to create the ATM implied volatility for each maturity. Finally, VXO is obtained by interpolating between the shortest and second shortest ATM implied volatility.

A-2 Construction of the new VIX index

In 2003 the construction algorithm of VIX changed along two dimensions. First, the underlying stock index of the new VIX index is S&P 500 and not S&P 100. Second, the new VIX index is constructed from prices of out-of-the-money (OTM) calls and puts as opposed to implied volatilities extracted from ATM options. This is advantageous since VIX is obtained in model-free way in the sense that it consistent with a very general class of processes for the underlying asset [see Jiang and Tian (2005) and Carr and Wu (2006)]. More specifically, the construction algorithm of the new VIX is based on the concept of model-free implied variance proposed by Britten-Jones and Neuberger (2000).[32] So, VIX is calculated by using the following equation:

$$\sigma_{t,T}^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{rT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \tag{A.1}$$

where $\sigma_{t,T} = \frac{VIX_t^2}{100}$, T is the time to maturity measured in minutes, F is the forward index level derived from ATM option prices, K_0 is the first strike below the forward index level F, K_i is the strike price of i-th out-of-the-money option (i.e. a call if $K_i > K_0$ and a put if $K_i < K_0$; both put and call if $K_i = K_0$), $\Delta K_i = ½ (K_{i+1} - K_{i-1})$ is the interval between strike prices, r is the risk free rate of interest, $Q(K_i)$ is the mid-point of the bid-ask spread for each option with strike K_i. Equation (A.1) is used to calculate σ_t^2 at two maturities, T_1 and T_2, that bracket a 30 calendar day period. Then, VIX is obtained by interpolating between σ_{t,T_1} and σ_{t,T_2} so that it corresponds to 30 days to maturity.

Implied volatility index	**Underlying asset**	**τ**	**K_i**	**Market**
VIX	S&P 500	30 calendar days	-	U.S.
VXO	S&P 100	30 calendar days	ATM	U.S.
VXN	NASDAQ 100	30 calendar days	-	U.S.
VXD	DJIA	30 calendar days	-	U.S.
VDAX-NEW	DAX 30	30 calendar days	-	Germany
VCAC	CAC 40	30 calendar days	-	France
VAEX	AEX	30 calendar days	-	Netherlands
VBEL	BEL 20	30 calendar days	-	Belgium
VSMI	SMI	30 calendar days		Switzerland
VSTOXX	EURO STOXX 50	30 calendar days	-	Euro-zone

Table A.1: European and U.S. implied volatility indices. The entries summarize the implied volatility indices on major European and U.S. equity indices. τ denotes the time to maturity and K the moneyness of the respective implied volatility index.

[32] The construction algorithm of all implied volatility indices but VXO is actually based on the concept of the fair value of the variance swap rate suggested by Demeterfi et al. (1999b, 1999a). Jiang and Tian (2007) have shown that this concept is equivalent to the model-free implied variance (see Appendix C). This holds even in the case that asset prices follow a jump-diffusion process.

Appendix B: Interpretation of implied volatility indices

In this Appendix the interpretation of implied volatility indices is considered. First, the interpretation of an implied volatility index as the investors' fear gauge is discussed [Whaley (2000)]. Second, the fact that an implied volatility index can be regarded either as a volatility or a variance swap rate depending on its construction algorithm is considered [see Carr and Wu (2006)]. In particular, we show that VXO and VIX^2 can be interpreted as a volatility and variance swap rate, respectively.

B-1 Investors' fear gauge

An implied volatility index can be interpreted as the investors' fear gauge [Whaley (2000)]. This is because, implied volatility indices take high values during periods of financial turmoil and high uncertainty (see e.g., Figure B.1 for VIX). The interpretation of implied volatility indices as investors' fear gauge is also justified on the observed negative contemporaneous relationship between implied volatility indices and the underlying stock indices, since in the case that the investors' fear is high, the required rate of return is also elevated and hence, stock prices fall. For instance, in Figure B.2 we can see in that upward (downward) spikes in VIX coincide with downward (upward) spikes in the S&P 500.

B-2 VXO as a volatility swap rate

In what follows, the interpretation of VXO as a volatility swap rate is discussed. Note that, VXO tracks the implied volatility of a synthetic ATM option. Thus, it suffices to show that the volatility swap rate can be approximated by ATM implied volatility [see also Carr and Wu (2006)].

B-2.1 The volatility swap rate: Definition

A volatility swap contract is a forward contract on annualized volatility, whose payoff at expiration is:

$$\left(V_{0,T} - VolSR\right) \times N$$

where $V_{0,T}$ is the realized stock volatility at expiration, *VolSR* is the delivery price for volatility swap contract and *N* is the notional amount of the swap in dollars per annualized volatility point. The price of a volatility swap is:

$$F_0 = e^{-rT} E^Q \left(V_{0,T} - VolSR \right) \tag{B.1}$$

where *Q* denotes the risk-neutral probability measure, *r* the risk free rate of interest and *T* the expiration date. Thus, the *fair delivery price* or *volatility swap rate*, *VolSR*, is determined so that the contact has zero value:

$$0 = e^{-rT} E^Q \left(V_{0,T} \right) - e^{-rT} E^Q \left(VolSR \right)$$

$$\Leftrightarrow \qquad VolSR = E^Q \left(V_{0,T} \right) \tag{B.2}$$

B-2.2 Approximating the volatility swap rate with ATM implied volatility

Under certain assumptions Hull and White (1987) have shown that the value of a call option can be written as the expected Black and Scholes (1973) price under the risk neutral probability measure evaluated at the realized variance, $V_{0,T}^2$. This means that the price of an ATM forward call option is given in this case by the following equation:[33]

$$C^{ATM} = E^Q \left\{ F \left[N(d_1) - N(d_2) \right] \right\} \tag{B.3}$$

where $d_1 = \frac{V_{0,T}}{2}\sqrt{T} = -d_2$. Taking a Taylor series expansion of the cumulative standard normal distribution around zero yields [see Brenner and Subrahmanyam (1988)]:

$$N(d_1) = \frac{1}{2} + \frac{1}{\sqrt{2\pi}} \left(d_1 - \frac{d_1^3}{3!} + \frac{d_1^5}{5!} - \ldots \right) \tag{B.4}$$

Thus, using equation (B.4) we have:

$$\begin{aligned} N(d_1) - N(d_2) &= N(d_1) - N(-d_1) \\ &= N(d_1) - \left[1 - N(d_1) \right] \\ &= 2N(d_1) - 1 \end{aligned}$$

[33] An ATM forward call option is an option that has a strike price, *K*, equal to the forward price, F_t, i.e. $K = F_t$.

$$= \frac{2}{\sqrt{2\pi}} \left(d_1 - \frac{d_1^3}{3!} + \frac{d_1^5}{5!} - \ldots \right)$$

$$= \frac{V_{0,T}}{\sqrt{2\pi}} \sqrt{T} + O\left(T^{3/2}\right) \qquad \text{(B.5)}$$

Next, substituting (B.5) into (B.4) yields:

$$C^{ATM} = E^Q \left\{ F \frac{V_{0,T}}{\sqrt{2\pi}} \sqrt{T} + O\left(T^{3/2}\right) \right\}$$

$$\Leftrightarrow \qquad E^Q \left(V_{0,T}\right) = \frac{\sqrt{2\pi}}{F_t \sqrt{T}} C^{ATM} + O\left(T^{3/2}\right) \qquad \text{(B.6)}$$

Note also that the implied volatility of an ATM forward call option is given by the following equation:

$$C^{ATM} = FN\left(d_1\right) - Ke^{-rT} N\left(d_2\right)$$

$$\Leftrightarrow \qquad C^{ATM} = F\left[N\left(d_1\right) - N\left(d_2\right) \right] \qquad \text{(B.7)}$$

Substituting (B.5) into (B.7) gives:

$$C^{ATM} = F \frac{\sigma^{ATM}}{\sqrt{2\pi}} \sqrt{T} + O\left(T^{3/2}\right)$$

$$\sigma^{ATM} = \frac{\sqrt{2\pi}}{F\sqrt{T}} C^{ATM} + O\left(T^{3/2}\right) \qquad \text{(B.8)}$$

where σ^{ATM} is the implied volatility of the ATM call option. Next, subtracting (B.8) from (B.6) yields:

$$E^Q \left(V_{0,T}\right) = \sigma^{ATM} + O\left(T^{3/2}\right) \qquad \text{(B.9)}$$

Finally, comparing (B.2) and (B.9) we can see that the volatility swap rate is approximately equal to the ATM implied volatility:

$$VolSR = E^Q \left(V_{0,T}\right) \cong \sigma^{ATM}$$

This means that VXO can be interpreted as a volatility swap rate, since it tracks the implied volatility of a synthetic ATM option.

B-3 VIX2 as a variance swap rate

VIX^2 can be interpreted as a variance swap rate, i.e. as the delivery price of a variance swap contract [see Carr and Wu (2006)]. To understand why this is the case, the variance swap rate needs to be defined and an expression for its calculation has to be determined. Then, it suffices to show that the formula of VIX^2 and the variance swap rate are approximately the same.

B-3.1 The variance swap rate: Definition

A *variance swap* is a forward contract on annualized variance, whose payoff at expiration is:

$$\left(V_{0,T}^2 - VSR\right) \times N$$

where $V_{0,T}^2$ is the realized stock variance at expiration, *VSR* is the delivery price for variance and *N* is the notional amount of the swap in dollars per annualized variance point. The price of a variance swap is:

$$F_0 = e^{-rT} E^Q\left(V_{0,T}^2 - VSR\right) \tag{B.10}$$

where *Q* denotes the risk-neutral probability measure, *r* the risk free rate of interest and *T* the expiration date. Thus, the *fair delivery price* or *variance swap rate*, *VSR*, is determined so that the contact has zero value:

$$0 = e^{-rT} E^Q\left(V_{0,T}^2\right) - e^{-rT} E^Q\left(VSR\right)$$

$$\Leftrightarrow \qquad VSR = E^Q\left(V_{0,T}^2\right) \tag{B.11}$$

B-3.2 Calculating the variance swap rate for a continuous process

Next, we prove the formula for the variance swap rate of Demeterfi et al. (1999b, 1999a). To this end, assume that the underlying asset price follows a diffusion process:

$$\frac{dS_t}{S_t} = \mu\left(t,...\right)dt + \sigma\left(t,...\right)dZ_t \tag{B.12}$$

In this case, the realized variance is defined as:

$$V_{0,T}^2 = \frac{1}{T}\int_0^T \sigma(t,...)^2\, dt \tag{B.13}$$

Hence, from (B.11) and (B.13) we can see that thee variance swap rate is given by the following equation:

$$VSR = \frac{1}{T}E^Q\left(\int_0^T \sigma(t,...)^2\, dt\right) \tag{B.14}$$

By applying Itô's Lemma to (B.12) for $\ln(S_t)$ the subsequent equation is obtained:

$$d\ln S_t = \left\{\mu(t,...) - \frac{1}{2}\sigma(t,...)^2\right\}dt + \sigma(t,...)dZ_t \tag{B.15}$$

and subtracting equation (B.15) from (B.12) we get:

$$\frac{dS_t}{S_t} - d\ln S_t = \mu(t,...)dt + \sigma(t,...)dZ_t - \left(\mu - \frac{1}{2}\sigma(t,...)^2\right)dt - \sigma(t,...)dZ_t$$

$$\Leftrightarrow \quad \frac{dS_t}{S_t} - d\ln S_t = \frac{1}{2}\sigma(t,...)^2\, dt \tag{B.16}$$

Next, integrating equation (B.16) from 0 to T and using equation (B.13) we have:

$$\int_0^T \frac{dS_t}{S_t}dt - \int_0^T d\ln S_t dt = \frac{1}{2}\int_0^T \sigma(t,...)^2\, dt$$

$$\Leftrightarrow \quad \frac{1}{T}\left(\int_0^T \frac{dS_t}{S_t}dt - \ln\frac{S_T}{S_0}\right) = \frac{1}{T}\frac{1}{2}\int_0^T \sigma(t,...)^2\, dt$$

$$\Leftrightarrow \quad V_{0,T}^2 = \frac{2}{T}\left(\int_0^T \frac{dS_t}{S_t}dt - \ln\frac{S_T}{S_0}\right) \tag{B.17}$$

Equation (B.17) implies that the realized variance can be replicated by forming a portfolio that consists of a continuously rebalanced long position in $1/S_t$ of the underlying asset and a static position in a contract which pays at expiration the log-return of the stock over the entire period.[34] In order to obtain the variance swap rate [see equation (B.14)] the risk-neutral expectation of (B.17) is considered:

$$VSR = E^Q\left(V_{0,T}^2\right) = \frac{2}{T}E^Q\left(\int_0^T \frac{dS_t}{S_t}dt\right) - \frac{2}{T}E^Q\left(\ln\frac{S_T}{S_0}\right) \tag{B.18}$$

[34] A contract that pays at expiration the log-return of the stock over the entire period is known as the log contract and has been introduced by Neuberger (1994).

In the absence of arbitrage opportunities, we know that the first term of equation (B.18) is given by the following relationship:

$$E^{Q}\left(\int_0^T \frac{dS_t}{S_t}dt\right) = rT \qquad \text{(B.19)}$$

with r being the risk-free short rate. With respect to the second term of equation (B.18), the log-payoff may be decomposed in the following way:[35]

$$\ln\frac{S_T}{S_0} = \ln\frac{S_T}{S_*} + \ln\frac{S_*}{S_0}$$

$$\Leftrightarrow \quad -\ln\frac{S_T}{S_*} = -\frac{1}{S_*}\left(S_T - S_*\right) + \int_0^{S_*}\frac{1}{K^2}\max\left(K - S_T, 0\right)dK + \int_{S_*}^{\infty}\frac{1}{K^2}\max\left(S_T - K, 0\right)dK \qquad \text{(B.20)}$$

where S_* marks the boundary between OTM calls and puts. This means that a contract offering a log-payoff can be replicated by a portfolio consisting of a short position in $(1/S_*)$ forward contracts with delivery price S_*, a portfolio consisting of long positions in $(1/K^2)$ puts with strike prices $K \in [0, S_*]$ and a portfolio consisting of long positions in $(1/K^2)$ calls with strike prices $K \in [0, S_*]$.

Next, substituting equations (B.19) and (B.20) into equation (B.18) and considering that $S_T = S_0 e^{rT}$, the variance swap rate is given by the following equation:

---

[35] Assume that a continuum of strike prices is available for call and put options. Consider a portfolio $\Pi(t)$ that consists of $(1/K^2)$ OTM call and put options. At time t the value of the portfolio is:

$$\Pi(t) = \int_0^{S_*}\frac{1}{K^2}P(K)dK + \int_{S_*}^{\infty}\frac{1}{K^2}C(K)dK$$

At expiration (t = T), the portfolio yields the following payoff:

$$\Pi(T) = \int_0^{S_*}\frac{1}{K^2}\max\left(K - S_T, 0\right)dK + \int_{S_*}^{\infty}\frac{1}{K^2}\max\left(S_T - K, 0\right)dK$$

Thus:

- If $S_T < S_*$ then:

$$\Pi(T) = \int_{S_*}^{S_T}\frac{1}{K^2}\left(S_T - K\right)dK = \int_{S_T}^{S_*}\left(\frac{1}{K} - \frac{S_T}{K^2}\right)dK = \left[\ln K + \frac{S_T}{K}\right]_{S_T}^{S_*} = \frac{1}{S_*}\left(S_T - S_*\right) - \ln\frac{S_T}{S_*}$$

- If $S_T > S_*$ then:

$$\Pi(T) = \int_{S_*}^{S_T}\frac{1}{K^2}\left(S_T - K\right)dK = \left[-\frac{S_T}{K} - \ln K\right]_{S_*}^{S_T} = \left(\frac{S_T}{S_*} - 1\right) - \ln\frac{S_T}{S_*} = \frac{1}{S_*}\left(S_T - S_*\right) - \ln\frac{S_T}{S_*}$$

Hence:

$$-\ln\frac{S_T}{S_*} = -\frac{1}{S_*}\left(S_T - S_*\right) + \int_0^{S_*}\frac{1}{K^2}\max\left(K - S_T, 0\right)dK + \int_{S_*}^{\infty}\frac{1}{K^2}\max\left(S_T - K, 0\right)dK$$

$$VSR = \frac{2}{T}\left\{ rT - \left(\frac{S_0 e^{rT}}{S_*} - 1 \right) - \log \frac{S_*}{S_0} + e^{rT} \int_0^{S_*} \frac{1}{K^2} P(K) dK + e^{rT} \int_{S_*}^{\infty} \frac{1}{K^2} C(K) dK \right\} \tag{B.21}$$

where $P(K)$ and $C(K)$ are put and call prices. Equation (B.21) is the formula of Demeterfi et al. (1999b, 1999a) for the variance swap rate.

B-3.2 VIX^2 and the variance swap rate

Next, we will show that VIX^2 [see equation (A.1)] is approximately equal to the variance swap rate of Demeterfi et al. (1999b, 1999a) [see equation (B.21)]. To this end, note that the integral terms in (B.21) can be interpreted as a portfolio consisting of $\left(1/K^2 \right)$ OTM options for a continuum of strikes. The remaining part in (B.21), termed *A*, is given by the following equation:

$$\begin{aligned}
A &= \frac{2}{T}\left\{ rT - \left(\frac{S_0 e^{rT}}{S_*} - 1 \right) - \log \frac{S_*}{S_0} \right\} \\
&= \frac{2}{T}\left\{ rT - \left(\frac{S_0 e^{rT}}{S_*} - 1 \right) - \log \frac{S_* e^{rT}}{S_0 e^{rT}} \right\} \\
&= \frac{2}{T}\left\{ rT - \left(\frac{F_0}{S_*} - 1 \right) - \log \frac{S_*}{F_0} - \ln e^{rT} \right\} \\
&= \frac{2}{T}\left\{ - \left(\frac{F_0}{S_*} - 1 \right) + \log \frac{F_0}{S_*} \right\}
\end{aligned} \tag{B.22}$$

Similarly, the first term in equation (A.1) is a portfolio consisting of $\left(1/K^2 \right)$ OTM options for discrete strikes. The remaining part in equation (A.1), termed *B*, is equal to:

$$B = -\frac{1}{T}\left(\frac{F}{K_0} - 1 \right)^2 \tag{B.23}$$

Thus, for VIX^2 to be interpreted as a variance swap rate it suffices to show that $A = B$. Indeed, it can be shown that B is an approximation of A, by expanding the log-function in A [equation(B.24)] around 1:[36]

$$\log\frac{F_0}{S_*} \cong \log(1) + \left[\frac{1}{F_0/S_*}\right]_{S_*=F_0}\left(\frac{F_0}{S_*}-1\right) + \frac{1}{2}\left[-\frac{1}{\left(F_0/S_*\right)^2}\right]_{S_*=F_0}\left(\frac{F_0}{S_*}-1\right)^2$$

$$\cong \left(\frac{F_0}{S_*}-1\right) - \frac{1}{2}\left(\frac{F_0}{S_*}-1\right)^2 \qquad \text{(B.25)}$$

Finally, from (B.22), (B.23) and (B.25) we that:

$$A \cong \frac{2}{T}\left\{-\left(\frac{F_0}{S_*}-1\right) + \left(\frac{F_0}{S_*}-1\right) - \frac{1}{2}\left(\frac{F_0}{S_*}-1\right)^2\right\} = -\frac{1}{T}\left(\frac{F_0}{S_*}-1\right)^2 = B$$

Thus, VIX^2 can be interpreted as a variance swap rate.

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[36] The Taylor series expansion around 1 of $\log\frac{F_0}{S_*}$ is:

$$\log\frac{F_0}{S_*} \cong \log(1) + \left[\frac{1}{F_0/S_*}\right]_{S_*=F_0}\left(\frac{F_0}{S_*}-1\right) + \frac{1}{2}\left[-\frac{1}{\left(F_0/S_*\right)^2}\right]_{S_*=F_0}\left(\frac{F_0}{S_*}-1\right)^2 \cong \left(\frac{F_0}{S_*}-1\right) - \frac{1}{2}\left(\frac{F_0}{S_*}-1\right)^2$$

Hence: $A \cong \frac{2}{T}\left\{-\left(\frac{F_0}{S_*}-1\right) + \left(\frac{F_0}{S_*}-1\right) - \frac{1}{2}\left(\frac{F_0}{S_*}-1\right)^2\right\} = -\frac{1}{T}\left(\frac{F_0}{S_*}-1\right)^2 = B$.

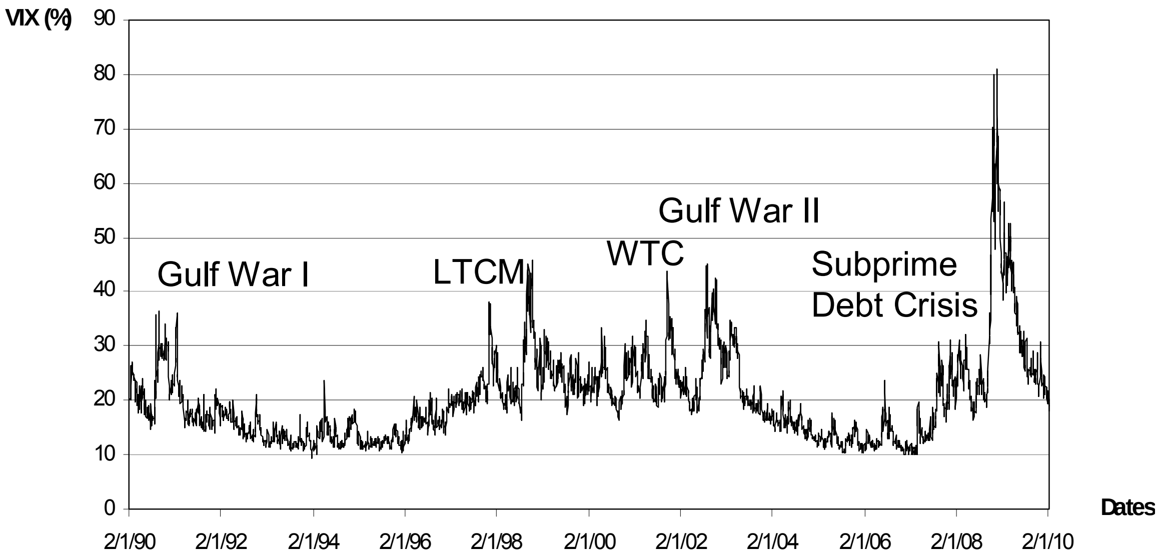

Figure B.1: Evolution of VIX (%) over the period February 2, 2001 to January 8, 2010.

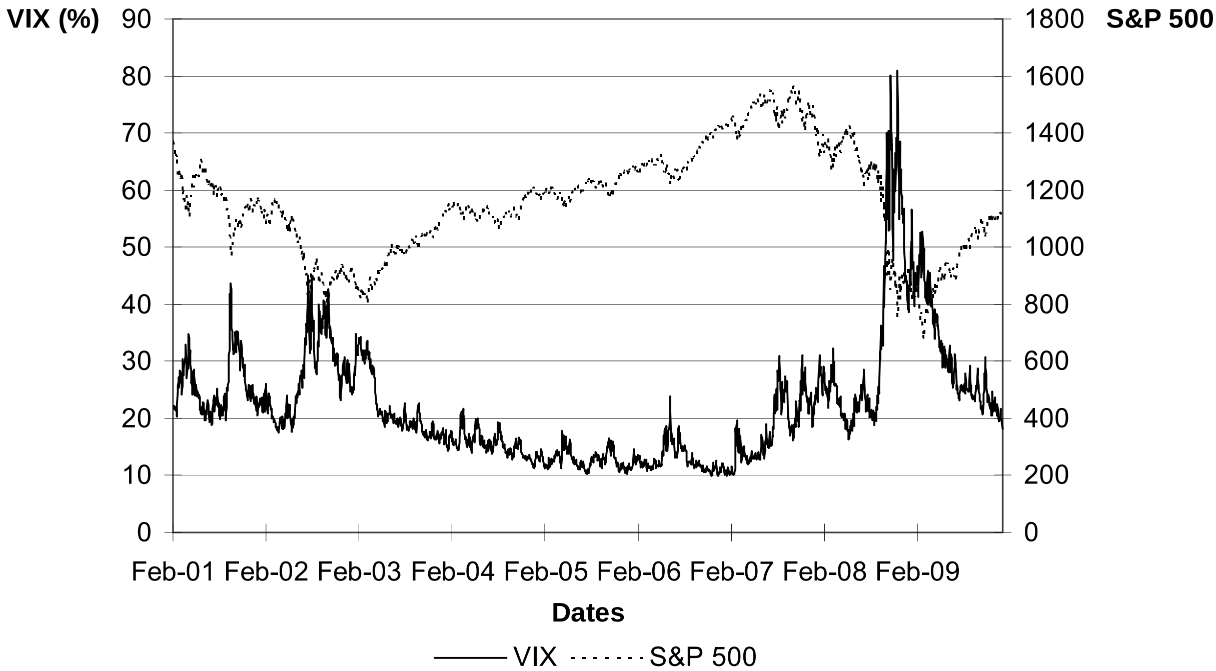

Figure B.2: Evolution of VIX (%, solid line) and the S&P 500 (dotted line) over the period February 2, 2001 to January 8, 2010.

Appendix C: Model-free implied variance and variance swap rate

In this Appendix it is proved that the concept of the variance swap rate is equivalent to the model-free implied variance proposed by Britten-Jones and Neuberger (2000) [see also Jiang and Tian (2005)]. This is important because it implies that the construction algorithm of VIX is model free; VIX^2 is approximately equal to the variance swap rate (see Appendix B) and the variance swap rate is equivalent to the model-free implied variance.

To fix ideas, the model-free implied variance proposed by Britten-Jones and Neuberger (2000) is given by the following equation:[37]

$$E^Q\left[\int_0^T\left(\frac{dS_t}{S_t}\right)^2\right]=\frac{2}{T}\int_0^\infty\frac{e^{rT}C(T,K)-\max\left(S_0e^{rT}-K,0\right)}{K^2}dK \tag{C.1}$$

$$=\frac{2}{T}\left[\int_0^{S_0e^{rT}}\frac{e^{rT}C(T,K)-\max\left(S_0e^{rT}-K,0\right)}{K^2}dK+\int_{S_0e^{rT}}^{\infty}\frac{e^{rT}C(T,K)-\max\left(S_0e^{rT}-K,0\right)}{K^2}dK\right]$$

$$=\frac{2}{T}\left[\int_0^{S_0e^{rT}}\frac{e^{rT}C(T,K)-S_0e^{rT}+K}{K^2}dK+\int_{S_0e^{rT}}^{\infty}\frac{e^{rT}C(T,K)}{K^2}dK\right] \tag{C.2}$$

where $C(T, K)$ is price of a call option that matures at T and has a strike price equal to K, S_0 is the price of the underlying asset at $t = 0$ and r is the risk free rate of interest . Using the put-call parity [$C(T,K)+Ke^{-rT}=P(T,K)+S_0$ where $P(T, K)$ is price of a put option that matures at T and has a strike price equal to K], equation (C.2) becomes:

$$E^Q\left[\int_0^T\left(\frac{dS_t}{S_t}\right)^2\right]=\frac{2}{T}\left[\int_0^{S_0e^{rT}}\frac{e^{rT}P(T,K)}{K^2}dK+\int_{S_0e^{rT}}^{\infty}\frac{e^{rT}C(T,K)}{K^2}dK\right]$$

$$=\frac{2e^{rT}}{T}\left[\int_0^{S_0e^{rT}}\frac{P(T,K)}{K^2}dK+\int_{S_0e^{rT}}^{\infty}\frac{C(T,K)}{K^2}dK\right]$$

[37] The model-free implied variance proposed by Britten-Jones and Neuberger (2000) is actually given be the following equation:

$$E^Q\left[\int_0^T\left(\frac{dS_t}{S_t}\right)^2\right]=2\int_0^\infty\frac{C(T,K)-\max\left(S_0-K,0\right)}{K^2}dK$$

However, Jiang and Tian (2005) have shown that this is equivalent to (C.1). This holds even in the case that asset prices follow a jump-diffusion process.

$$= \frac{2e^{rT}}{T}\left[\int_0^{S_*} \frac{P(T,K)}{K^2} dK + \int_{S_*}^{S_0 e^{rT}} \frac{P(T,K)}{K^2} dK + \int_{S_0 e^{rT}}^{S_*} \frac{C(T,K)}{K^2} dK + \int_{S_*}^{\infty} \frac{C(T,K)}{K^2} dK \right]$$

$$= \frac{2e^{rT}}{T}\left[\int_0^{S_*} \frac{P(T,K)}{K^2} dK + \int_{S_*}^{\infty} \frac{C(T,K)}{K^2} dK + \int_{S_*}^{S_0 e^{rT}} \frac{P(T,K) - C(T,K)}{K^2} dK \right] \tag{C.3}$$

Using the put-call parity again, equation (C.3) becomes:

$$E^Q\left[\int_0^T \left(\frac{dS_t}{S_t} \right)^2 \right] = \frac{2e^{rT}}{T}\left[\int_0^{S_*} \frac{P(T,K)}{K^2} dK + \int_{S_*}^{\infty} \frac{C(T,K)}{K^2} dK + \int_{S_*}^{S_0 e^{rT}} \frac{Ke^{-rT} - S_0}{K^2} dK \right]$$

$$= \frac{2}{T}\left[e^{rT} \int_0^{S_*} \frac{P(T,K)}{K^2} dK + e^{rT} \int_{S_*}^{\infty} \frac{C(T,K)}{K^2} dK + \int_{S_*}^{S_0 e^{rT}} \frac{K - S_0 e^{rT}}{K^2} dK \right] \tag{C.4}$$

Next, calculating the third interval in (C.4) yields:[38]

$$E^Q\left[\int_0^T \left(\frac{dS_t}{S_t} \right)^2 \right] = \frac{2}{T}\left[e^{rT} \int_0^{S_*} \frac{P(T,K)}{K^2} dK + e^{rT} \int_{S_*}^{\infty} \frac{C(T,K)}{K^2} dK + rT - \ln\left(\frac{S_*}{S_0} \right) - \left(\frac{S_0 e^{rT}}{S_*} - 1 \right) \right] \tag{C.5}$$

Finally, by comparing (B.21) and (C.5) we can see that the variance swap rate and the model free implied variance are equivalent:

$$E^Q\left[\int_0^T \left(\frac{dS_t}{S_t} \right)^2 \right] = VSR$$

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[38] The third integral is calculated in the following way:

$$\int_{S_*}^{S_0 e^{rT}} \frac{K - S_0 e^{rT}}{K^2} dK = \int_{S_*}^{S_0 e^{rT}} \frac{1}{K} dK - S_0 e^{rT} \int_{S_*}^{S_0 e^{rT}} \frac{1}{K^2} dK = \ln K \Big|_{S_*}^{S_0 e^{rT}} - S_0 e^{rT} \left[-\frac{1}{K} \Big|_{S_*}^{S_0 e^{rT}} \right] = rT + \ln(S_0 / S_*) + 1 - \frac{S_0 e^{rT}}{S_*}$$

Appendix D: Testing the MCP by using the ratio test

One of the statistical metrics under which the out-of-sample performance of the employed models is assessed is the mean correct prediction (MCP). All models under consideration are compared to the random walk model that is used as a benchmark. Strictly speaking, the MCP cannot be calculated under the random walk model. Hence, in the ratio test, the random walk model is treated as a naïve model that would yield MCP = 50%. Thus, in order to assess the out-of-sample performance of the employed models, the following hypothesis is tested:

$$H_0 : MCP = 50\%$$

$$H_\alpha : MCP > 50\%$$

or equivallently H_0 : The model and the random walk perform equally well.

H_α The model outperforms the random walk.

This hypothesis is tested by using the ratio test statistic, *T*, that is given by the following equation:

$$T = \frac{\frac{X}{n} - 0.5}{\sqrt{\frac{0.5 \times 0.5}{n}}} \tag{D.1}$$

where *X* is the number of times that the predicted and the actually observed sign of the change are the same (i.e. the number of successes in a Bernoulli sequence) and *n* is the number of observations. Note that $\hat{p} = \frac{X}{n}$ is an estimator of the % of successes. Under the null hypothesis, the test statistic follows approximately a normal distribution, *N*(0,1). This means that the model under consideration performs better than the naïve rule at when $T > Z_{1-a}$ an *a*% level of significance.

Appendix E: Monte Carlo simulation for Christoffersen (1998) test

To evaluate the goodness of the out-of-sample interval forecasts, Christoffersen's (1998) likelihood ratio test of unconditional coverage (LR_{unc}) is used. Given that the power of this test may be sensitive to the sample size, we base the accept/reject decisions of the null hypothesis on Monte Carlo (MC) simulated *p*-values which are obtained through the following algorithm [see Christoffersen (2003)]:

- **Step 1:** Simulate a sample of *n* random independent and identically distributed (i.i.d.) Bernoulli (*a*) variables.
- **Step 2:** Calculate the test statistic, $LR_{unc}^{simulated}$, for the simulated sample.
- **Step 3:** Repeat steps 1 and 2 $B = 9{,}999$ times. This yields the simulated distribution of the test statistic.
- **Step 4:** Construct an indicator variable that takes the value 1 if $LR_{unc}^{simulated}$ exceeds LR_{unc} from the actual sample and 0 otherwise, and calculate *M* as the sum of this indicator variable. *M* shows the number that the simulated test statistics exceed the actually observed one.
- **Step 5:** Calculate the Monte Carlo p-value in the following way:

$$p-value = \frac{1+M}{1+B}$$

Appendix F: Stationary bootstrap hypothesis testing

The stationary bootstrap of Politis and Romano (1994) is applicable to weakly dependent stationary time series. It involves re-sampling *blocks* of random size from the original time series to form a pseudo time series (or a bootstrapped sample). The block size follows a geometric distribution with mean block length $1/q$. The main feature of this procedure is that the re-sampled pseudo time series retains the stationarity property of the original series.

To fix ideas, let $\{X_t, t \in Z\}$ be a strictly stationary and weakly dependent time series (t = 1, 2, …N). In addition, let $B_{i,b} = \{X_i, X_{i+1}, ..., X_{i+b-1}\}$ be a block consisting of b observations starting from X_i [for $j>N$, $X_j \equiv X_i$ with $i = j(\text{mod } N)$ and $X_0 = X_N$] where $i = I_1, I_2$ … is a sequence of i.i.d. random variables that have a uniform distribution on {1, …, N} that is independent of X_i, and $b = L_1, L_2$ … is a sequence of i.i.d. random variables that have a geometric distribution (p) with p being a fixed number in [0,1] that is independent of X_i, and I_i. Then, the bootstrapped p-value of the test statistic under consideration is calculated in the following way:

- **Step 1:** Generate a bootstrap sample by sampling a sequence of blocks of random length B_{I_1,L_1}, B_{I_2,L_2}, …. The first L_1 observations are X_{I_1}, … $X_{I_1+L_1-1}$, the next L_2 observations are X_{I_2}, … $X_{I_2+L_2-1}$ etc. Stop once N observations in the bootstrap sample have been generated.
- **Step 2:** Calculate the test statistic for the bootstrapped sample.
- **Step 3:** Repeat steps 1 and 2 B times. This yields the bootstrapped distribution of the test statistic.
- **Step 4:** Construct an indicator variable that takes the value 1 if the bootstrapped test statistic is more extreme from the actually observed test statistic and 0 otherwise, and calculate M as the sum of this indicator variable. M shows the number that the bootstrapped test statistics is more extreme than the actually observed one.
- **Step 5:** Calculate the bootstrapped p-value in the following way: $p - value = \frac{1+M}{1+B}$

Appendix G: Bootstrapping interval forecasts

In order to take into account the potential non-normality of a model's residuals and the parameter uncertainty, interval forecasts are formed by applying the bootstrap methodology. More specifically, the methodology suggested by Pascual et al. (2001) is adopted. This methodology is advantageous since in the case of ARMA models it does not require the existence of the backward representation of the process. Based on Pascual et al. (2001) the bootstrapped interval forecasts are obtained through the following algorithm:

- **Step 1:** Estimate the model under consideration and retain the rescaled and centered residuals, ε.
- **Step 2:** Generate a bootstrap sample of the residuals $\varepsilon^* = \left(\varepsilon^*_{q+1},...,\varepsilon^*_n\right)$ by using sampling with replacement.
- **Step 3:** Construct the bootstrap replicate of the series to be forecasted by using the estimated coefficients of the model under consideration and the bootstrapped residuals from step 2.
- **Step 4:** Obtain the bootstrap coefficients by estimating the model under consideration for the bootstrap replicate of the series constructed in step 3.
- **Step 5:** Form the one step ahead bootstrap forecast by using the bootstrap coefficients from step 4.
- **Step 6:** Repeat steps 1 to 5 B times. This yields the simulated distribution of the one step ahead bootstrapped forecasts.
- **Step 7:** Find the $\left(a/2\right)100th$ and $\left(1-a/2\right)100th$ percentile of the empirical distribution.