Can the Evolution of Implied Volatility be Forecasted? Evidence from European and U.S. Implied Volatility Indices*

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Abstract

We address the question whether the evolution of implied volatility can be forecasted by studying a plethora of European and U.S. implied volatility indices. The statistical accuracy of point and interval forecasts is examined by alternative model specifications. The economic significance of the predictions is also assessed by trading games in the recently inaugurated CBOE volatility futures markets. Regarding the point forecasts, the in-sample statistical evidence suggests that the degree of predictability differs among indices and also depends on the choice of model and forecasting horizon. However, the considered models do not outperform the random walk model in an out-of-sample setting. The interval forecasts have no predictive power either. The trading games reveal that no economically significant profits can be attained.

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Keywords: Implied volatility, Implied volatility indices, Interval forecasts, Market efficiency, Predictability, Volatility futures.

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1. Introduction

The question whether the dynamics of implied volatility per se can be forecasted is of paramount importance to both academics and practitioners[1]. On any given point in time, implied volatility is the volatility that equates the market option price with the Black-Scholes (1973) option price. It has been well documented that on any given date, implied volatilities depend on the strike price and maturity of the option under scrutiny giving rise to a non-flat implied volatility surface. In addition, this surface changes over time. Given that the implied volatility is a reparameterisation of the market option price, the issue of whether it's evolution is predictable falls within the vast literature on the predictability of asset prices (see e.g., Campbell et al., 1997, and the references therein). 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 there is a predictable variation in implied volatility can help us understand how expected returns change over time. 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.

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. Dumas et al. (1998) and Gonçalves and Guidolin (2006) have investigated whether the dynamics of the S&P 500 implied surface can be predicted over different time periods. The first study finds that the specifications under scrutiny are unstable over time for the purposes of option pricing and hedging. The second finds a statistically predictable pattern. However, for given trading strategies, this pattern cannot be exploited in an economically significant way since no abnormal profits can be obtained as transaction costs increase. There is also some literature that has explored whether the evolution of short-term at-the-money implied volatility, rather than the entire implied volatility surface, can be forecasted over time in various markets. Harvey and Whaley (1992), Guo (2000) and Brooks and

[1] This question is distinct from the questions that ask whether implied volatility can forecast the future realised volatility and whether the evolution of volatility measured as the standard deviation of past returns is predictable (see Granger and Poon, 2003, for an excellent survey of this literature). 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 Alexander, 2001, for an excellent review).

Oozeer (2002) have addressed this question in the S&P 100, Philadelphia Stock Exchange currency, and LIFFE long gilt futures options markets, respectively. To this end, they used sets of economic variables (e.g., index returns, short-term interest rate, slope of the term structure of interest rates, etc.) and the lagged values of implied volatility as predictors. They found that changes in implied volatility are partially statistically predictable. However, their results are not economically significant just as in Gonçalves and Guidolin (2006). 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 (US) options are employed. However, the economic significance of their results is not examined. On the other hand, Goyal and Saretto (2006) have found that there is both a statistically and economically significant predictable pattern in the dynamics of implied volatility by using information from the cross-section of implied volatilities across various stock options.

This paper makes at least five 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 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; Fama and French (1988b) for instance, have found that the firm size affects the magnitude of predictability in stock markets. 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; Poon and Pope (2000) have found that profitable volatility spread trades can be developed in the index option S&P 100 and S&P 500 option markets by constructing certain intervals. 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 (see also Han, 2006, for a similar approach in the setting of stock return predictability). Fourth, the economic significance of the statistical evidence is assessed by means of trading games in the newly introduced and fast growing CBOE volatility futures markets. The results will have implications about the efficiency of these markets in the spirit of the definition of market efficiency provided by Jensen (1978). To the best of our knowledge, the efficiency of these markets has not yet been investigated. Finally, the paper examines whether the degree of predictability in implied volatility depends on the horizon under scrutiny by considering daily as well as monthly horizons; most of the options' trading activity is concentrated in short horizons. It has been well documented that the predictability in asset returns increases as the horizon increases (see e.g., Fama and French, 1988a, 1988b, Poterba and Summers, 1988). The previously mentioned empirical studies on implied volatilities have not addressed the impact of the horizon on their reported results.

To fix ideas, an implied volatility index tracks the implied volatility of a synthetic option that has constant time-to-maturity (and usually a fixed strike). Implied volatility indices have mushroomed over the last 15 years in the European and U.S. markets. The data on the implied volatility indices are the natural choice to study the dynamics of the market implied volatility. This is because the various methods to construct the index are informative and precise. They take as input the implied volatilities/market prices of options with various strikes and expiries, and they "average" them so as to minimize the notorious measurement errors in implied volatilities (see e.g., Hentschel, 2003). Moreover, predicting 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[2]. In addition, they affect the pricing and hedging of variance/volatility swaps; an implied volatility index can be interpreted as the variance/volatility swap rate (see Carr and Lee, 2005, and Carr and Wu, 2006) that affects the market value of these volatility derivatives (Chriss and Morokoff, 1999). Furthermore, the implied volatility index can also be used for Value-at-Risk purposes (Giot, 2005a), to identify buying/selling opportunities in the stock market (Copeland and Copeland, 1999, Whaley, 2000, Giot, 2005b, Banerjee et al., 2007), and to forecast the future market volatility (see e.g., Fleming et al., 1995, Moraux et al., 1999, Simon, 2003, Corrado and Miller, 2005, Giot, 2005a, Becker et al., 2007).

Daouk and Guo (2004), Wagner and Szimayer (2004), and Dotsis et al. (2007) have studied the dynamics of implied volatility indices for the purposes of pricing implied volatility derivatives. 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) and Ahoniemi (2006) are the only related studies. Both studies are conducted in a daily horizon setting and they focus on a limited number of indices. The first paper

[2] The payoff of an implied volatility derivative is similar to that of a plain vanilla option where the underlying asset is the implied volatility index. Implied volatility derivatives have been developed to trade and hedge against changes in volatility (see Dotsis et al., 2007, for a review of the literature). They had been trading over the counter for a long time and recently they have also been introduced in major exchanges. CBOE launched the first futures contract on VIX in March 2004. In April 2005 it launched futures on the implied volatility index VXN and in February 2006 options on VIX. In September 2005, the European derivatives market Eurex introduced futures on VSTOXX, on VDAX-NEW and on VSMI.

examines the presence of spillover effects between the VIX, VDAX and the VX1 implied volatility indices over the period 1994-1999; the author finds that these three indices interact with each other on a lagged basis. The second employs only the VIX data set by using various parametric models to provide point forecasts and then a trading game with the S&P 500 options is performed. The author performs her analysis over the period 1990-2002, as well as for sub-periods. The statistical evidence depends on the period under scrutiny and the trading game reveals that any degree of statistical predictability is not economically significant.

Our research approach is more general; a plethora of European and U.S. implied volatility indices is employed, point and interval forecasts are formed, trading games with VIX and VXD futures are constructed, and the predictability is examined in daily and monthly horizons. In particular, we evaluate the quality of point forecasts by means of predictive regressions. Alternative parametric and non-parametric specifications are considered. Within the parametric ones, first a set of economic variables is used as predictors, in line with the previous literature on the predictability of implied volatility[3]. Then, motivated by Gemmill and Kamiyama (2000), vector autoregressive schemes are also employed. Finally, the non-parametric specification is formed by using the principal components extracted from Principal Components Analysis as predictors; Stock and Watson (2002a) first suggested this approach and developed the underlying econometric theory (see also Stock and Watson, 2002b, and Artis et al., 2005, among others, for empirical applications of this idea to macroeconomic variables). The point forecasts are evaluated both in and out-of-sample. In the case of the interval forecasts, historical and Monte Carlo (MC) simulation is also used. To perform MC simulation, a jump diffusion process is chosen in line with the findings of Dotsis et al. (2007) so as to account for the empirical regularities of implied volatility indices. The in-sample analysis of the point forecasts reveals that only the French indices are predictable in the daily horizons; some of the U.S. indices also become predictable in the monthly horizons. However, for any given index, the out-of-sample performance of the various models does not beat the forecasts provided by a random walk model. The interval forecasts have no predictive power either. Furthermore, the risk-adjusted performance of the trading games indicates that no economically significant returns can be attained once transactions costs are taken into account.

[3] A similar approach has also been used in the literature that is related to the predictability of stock market returns where various economic variables have been used as predictors (see for instance Goyal and Welch, 2007, and the references therein).

The remainder of the paper is structured as follows. In the next Section the data sets are described. Sections 3 to 6 form the point forecasts study. In particular, Section 3 considers certain economic variables and examines whether there is a contemporaneous and lagged relationship with each implied volatility index. Next, we check whether the presence of any spillover effects among the various markets can be exploited in a predictive setting. In Section 5, PCA is applied and the forecasting power of the extracted factors is presented. Section 6 examines the out-of-sample performance of the alternative model specifications. Section 7 describes the construction of the interval forecasts, evaluates their statistical accuracy and discusses the results from the trading games. Section 8 discusses the results from the analysis in monthly horizons. The last Section concludes and the implications of the research are outlined.

2. The Data Set

Daily data on eight 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. However, given that the VXN data are available since 2/02/2001, our spot market data span the period from 2/02/2001 to 8/01/2007 so as to study the eight indices over a common time period; the subset from 2/02/2001 to 17/03/2005 will be used for the in-sample evaluation and the remaining data will be used for the out-of-sample one. The volatility futures data cover the period from 18/03/2005 up to 8/01/2007.

In particular, four major American and four European implied volatility indices are examined: VIX, VXO, VXN, VXD, VDAX, VX1, VX6, and VSTOXX. The first four indices are published by CBOE. 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 is constructed from the implied volatilities of options on DAX (Germany), while VX1 and VX6 are constructed from the implied volatilities of options on CAC 40 (France). VSTOXX is constructed from the market prices of options on the DJ EURO STOXX 50 index. The data for VDAX are obtained from Bloomberg while for the other indices are obtained from the websites of the corresponding exchanges. VXO, VDAX, VX1 and VX6 represent the implied volatility of an at-the-money synthetic option with constant time-to-maturity at any point in time. The remaining indices represent the variance swap rate once they are squared[4]. The constant time to maturity is the same (thirty calendar days) for almost all indices under scrutiny. The only exceptions are VDAX (45 days) and VX6 (185 days- see also the web sites of the corresponding exchanges, as well as Dotsis et al., 2007, for further details on the construction of the indices). Moreover, we study the adjusted VXO, $VXOA = \sqrt{\frac{22}{30}} \times VXO$ rather than VXO itself. Carr and Lee (2005) and Carr and Wu (2006) have shown that this adjustment allows interpreting VXOA as the volatility swap rate under general assumptions. Therefore, the adopted adjustment enables us to study directly one of the key factors that affect the prices of volatility swaps (Chriss and Morokoff, 1999).

The set of economic variables consists of the corresponding stock indices, two short-term (one month) interbank interest rates, the USD Libor/Euribor rates, r^{US}, and r^{EU}, respectively, the exchange rate $fx^{€/\$}$ of Euro/USD, the prices O^{WTI} and O^{BRENT} of the WTI and Brent crude oil, respectively, the slope of the yield curve calculated as the difference between the prices of the 10-year (French/German/ U.S.) government bond and the one-month interbank interest rate for the French/German/U.S. and VSTOXX implied volatility indices, and the volume of the futures contract of the underlying stock index. The time series of the economic variables were downloaded from Datastream[5].

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 3/01/2007, the open interest for the VIX/ VXD futures had increased by 95%/ 133%. The underlying asset of the VIX/ VXD futures contract is an “Increased-Value index” (VBI/DVB) that is 10 times the value of VIX/ VXD at any point in time. The contract size of the volatility futures is \$100 times the value of the underlying index[6]. On any day, up to six near-term serial 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

[4] A variance/volatility swap is actually a forward contract where the buyer (seller) receives the difference between the realized variance/volatility of the returns of a stated index and a fixed variance/volatility rate, termed variance/volatility swap rate, if the difference is positive (negative).
[5] Data on the volume of the futures contract on the S&P 100 are not available since this contract is not traded.
[6] On March 26, 2007, CBOE rescaled the VIX and VXD futures contracts in two ways: the contract size was increased to \$1000 and the contracts were based directly on the underlying VIX and VXD volatility indices instead of using VBI and DVB. The amendment date is beyond the ending date of our sample.

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.

Table 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, Panels C and D, respectively). Information on the volume in the volatility futures markets is also provided. The Jarque-Bera test for normality and the augmented Dickey-Fuller (ADF) test for unit roots are also reported. We can see that the null-hypothesis of normality in the changes of implied volatility indices is rejected; the distribution of the changes of all indices but VXN is positively skewed. Interestingly, only the French indices exhibit a strong negative autocorrelation in the daily changes; this is evidence of mean reversion. 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 the economic variables (not reported here due to space limitations). Note that the VIX futures are more liquid that the VXD ones as expected.

3. Implied Volatility Index and Economic Variables

This section investigates whether a model that includes certain economic variables can forecast the evolution of each implied volatility index over time. This is done in two steps. First, we check the goodness-of-fit of the model in a contemporaneous setting and then in a predictive setting.

3.1 Economic Variables: Contemporaneous Relationship

Various studies have already explored the relationship of implied volatility with a number of economic variables in a contemporaneous setting (see e.g., Franks and Schwartz, 1991, Fleming et al., 1995, Whaley, 2000, Davidson et al., 2001, Mixon, 2002, Simon, 2003, Bollen and Whaley, 2004, and Giot, 2005b). In line with these studies, the following regression is employed:

$$\Delta IV_t = c_1 + a_0^+ R_t^+ + a_0^- R_t^- + \beta_0 i_t + \gamma_0 fx_t + \delta_0 oil_t + \zeta_0 \Delta HV_t + \kappa_0 \Delta ys_t + \xi_0 vol_t + \varepsilon_t \qquad (1)$$

where ΔIV_t denotes the daily changes of the implied volatility index, c_1 is a constant, and R^+_t, R^-_t denote the underlying stock index positive and negative log-returns, respectively; these two variables act as indicator functions (e.g., R^+_t is filled with the positive returns and zeroes elsewhere) so as to capture the possible presence of the asymmetric effect of index returns on implied volatility (see e.g., Simon, 2003, and Giot, 2005b, for a similar specification). 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 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. Log-differences/changes have been employed since the respective series are found to be non-stationary in the levels.

Theory, as well as related empirical evidence, suggests that these variables may potentially affect the value of an implied volatility index contemporaneously[7]. A negative relationship between the implied volatility index and the underlying stock returns (termed leverage effect) has been documented empirically; furthermore this relationship is asymmetric: negative index returns have a greater impact on implied volatility (see e.g., Fleming et al. 1995, Whaley, 2000, Simon, 2003, Giot, 2005b). Christie (1982) offered a theoretical explanation by stating that an increase in the equity of the firm decreases the debt to equity ratio and hence decreases volatility that measures the riskiness of the firm. The effect of a change of the interest rate on volatility is not clear; an increase in the interest rate decreases both the value of debt and equity. Therefore, the effect on the debt to equity ratio and hence on volatility is ambiguous. Regarding the effect of the other variables on implied volatility, an increase in the exchange rate (i.e. the domestic currency appreciates) is expected to decrease the implied volatility in the domestic economy. Similarly, an increase in oil prices increases the uncertainty in the economy and hence is expected to increase the implied volatility. The slope of the term structure of interest rates is incorporated since previous research has found that it affects stock returns and hence possibly option returns (see e.g., Chen et al., 1986). Finally, the volume is expected to be positively correlated with volatility (see e.g., Karpoff, 1987, for an extensive literature review, and Bollen and Whaley, 2004). The above mentioned set of economic variables is augmented by adding the changes of historical volatility as an explanatory variable. The historical volatility is calculated as a 30-day moving average of equally weighted past squared returns.

[7] This approach is similar to the one followed by Chen et al. (1986) who chose a set of economic factors that could possibly explain the behaviour of stock returns within the Arbitrage Pricing Theory.

Table 2 shows the estimated coefficients from regression (1) and the *t*-statistics within parentheses for each one of the eight implied volatility indices. Newey-West standard errors have been employed so as to correct for autocorrelation and heteroscedasticity in the residuals[8]. The regression model fits the data quite well. The adjusted R^2 ranges from 32%-68%. The contemporaneous returns of the underlying stock indices are statistically significant at the 1% level and negatively signed. This is consistent with the leverage effect hypothesis. In addition, negative returns have a greater impact to implied volatility than positive returns; this is also consistent with the findings of the previous literature. The remaining economic variables are statistically insignificant in the vast majority of cases; Franks and Schwartz (1991) had also documented the insignificance of exchange rates and oil prices by using weekly data on FTSE options. A few exceptions occur. The exchange rate and the oil price are statistically significant (negatively signed as expected) for VXN and VDAX, respectively. Similarly, the historical volatility and volume are significant for VXOA and VIX, VDAX, VSTOXX, respectively.

3.2 Economic Variables: Predictive Power

Given that regression (1) describes the data well, we next test whether it preserves the same goodness of fit in a predictive setting. This set of variables is enlarged by the term ΔIV_{t-1}; Harvey and Whaley (1992) and Guo (2000) have found this term to be statistically significant for the purposes of predicting implied volatility[9]. Furthermore, the choice of these variables is supported by the large literature on the predictability of asset returns. The expected index return appears in the expression of the conditional standard deviation of index returns; the implied volatility index is a measure of the latter (see also Harvey and Whaley, 1992, for this rational). Hence, the forecasting specification is

$$\begin{aligned}\Delta IV_t = c_1 + a_1^+ R_{t-1}^+ + a_1^- R_{t-1}^- + \beta_1 i_{t-1} + \gamma_1 fx_{t-1} + \delta_1 oil_{t-1} + \zeta_1 \Delta HV_{t-1} + \rho_1 \Delta IV_{t-1} + \\ + \kappa_1 \Delta ys_{t-1} + \xi_1 vol_{t-1} + \varepsilon_t\end{aligned} \tag{2}$$

Table 3 shows the estimated coefficients of model (2) and the Newey-West *t*-statistics within parenthesis for each one of the implied volatility indices under consideration. In contrast to the contemporaneous regression results, the adjusted R^2 is nearly zero for all but the French indices; VX1 and VX6 have adjusted $R^{2'}s$ equal to 15%

[8] We have also estimated all presented specifications by modeling the variance of the residuals as a GARCH process; various GARCH orders have been tested. These results are not reported since the GARCH models did not fit the data well.

[9] We have tested the forecasting model with higher lags for the autoregressive implied volatility term. However, the results in terms of the R^2 did not change.

and 19%, respectively. The CAC's positive return, and the previous day's change on VX1 are the significant variables for VX1. In the case of VX6, the interest rate and the previous day's change in VX6 are the statistically significant variables. Hence, mean reversion is a source of the predictability in the French indices (see also Dotsis et al., 2007, who have documented the existence of mean reversion in implied volatility indices) in a daily frequency. In the remaining indices almost all economic variables are insignificant. Harvey and Whaley (1992) had also found that interest rate variables and the lagged index returns cannot predict the future changes in the implied volatility of the S&P 100 options. Brooks (1998) had also found that the volume cannot predict the future changes of (the statistically measured) volatility. Interestingly, our results do not depend on the degree of capitalisation of the underlying stock index; for instance the S&P 500 index includes firms with smaller capitilisation than the firms included in the DJIA index. This 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, 1988b). 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, Torous et al., 2004). 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).

4. Implied Volatility Spillovers and Predictive Power

In this section we 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.

First, for each implied volatility index a univariate autoregression model is employed. An order of three lags is used since this minimises the Hannah-Quinn information criterion (within a range up to ten lags). The regressions have the form:

$$\Delta IV_t = c_1 + \sum_{j=1}^{3} \lambda_j \Delta IV_{t-j} + \varepsilon_t \tag{3}$$

Table 4 shows the results from the regressions given by model (3). We can see that the adjusted R^2 are very close to zero for almost all but the French implied volatility indices; the adjusted R^2 is 19% and 26% for VX1 and VX6, respectively. Next, a VAR model is employed so as to take into account the presence of any spillover effects among the various markets and check whether these can be used for forecasting purposes (see also Gemmill and Kamiyama, 2000). The VAR specification is given by

$$Y_t = C + \sum_{i=1}^{3} \Phi_i Y_{t-i} + u_t \qquad (4)$$

where Y_t is the vector of the eight implied volatility indices in their first differences that are assumed to be endogenously (jointly) determined. C is a (8×1) vector of constants, Φ_1, Φ_2, Φ_3 are (8×8) matrices of coefficients to be estimated, and ε_t is the vector of the VAR residuals.

Table 5 shows the results from the estimation of the VAR model by ordinary least squares (OLS). For each one of the eight equations in the VAR, the estimated coefficients are reported; one and two asterisks indicate that the estimated parameters are statistically significant at 1% and 5% level, respectively. The last row reports the adjusted R^2. The greatest adjusted R^2's are obtained for the French indices VX1 and VX6 (19% and 34%, respectively); the lowest are obtained for VIX and VXN (2% and 1%, respectively). A 10% fit is obtained for VDAX and VSTOXX and a 6% fit for VXOA and VXD. Interestingly, the VAR model fits in-sample the French data better compared with either the economic variables model [equation (2)] or the univariate autoregressive model [equation (3)]. This implies that spillover effects should be taken into account. In particular, focusing on the French indices, there are spillover effects between the two French indices and their European analogues VSTOXX and VDAX.

To ensure the reliability of the obtained results, the VAR model was tested for mis-specification. In particular, consistent OLS estimates of the population parameters are obtained as long as the residuals are serially uncorrelated and uncorrelated with the variables in the right hand side of equation (4), and the stability condition holds. We found that both conditions hold. Then, we confirmed that the VAR variables are endogenous by means of Granger-causality tests. Finally, the robustness of the VAR results was examined. To this end, we checked whether the selected group of variables to be incorporated in the VAR system affects the results to be obtained in terms of the R^2. Eight different vector auto-regression specifications are estimated: each time a variable was excluded from the original set of endogenous variables and the adjusted R^2 of every regression was recorded. We found that the exclusion of any implied volatility index from the set of endogenous variables does not affect the adjusted R^2 by more than +/-3% (see also Hamilton, 1994, for details on the VAR robustness tests).

5. Principal Components Analysis and Predictive Power

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). It has been used in a number of applications in asset allocation and option pricing and hedging (see e.g., Alexander, 2001, for a description of the method and financial applications). For the purposes of our analysis, the retained principal components are used as forecasting variables in a regression setting where the dependent variable is the implied volatility index under consideration. Stock and Watson (2002a) have shown that PCA can be employed to this end. 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 and general technique for forecasting purposes since it lets the data decide on the forecasting variables to be used. This is in contrast to the parametric approaches taken in Sections 3 and 4 where the set of forecasting variables was chosen a priori.

Once PCA is applied to the daily changes of implied volatility indices, four PCs are retained. The first four PCs explain 90% of the total variance of the changes of implied volatility indices. Interestingly, the first PC moves all the implied volatility indices to the same direction and hence it can be interpreted as a global factor. To identify any possible economic interpretation of the retained principal components, the pairwise correlations of the PCs with the economic variables employed in Section 3 are calculated (see also Mixon, 2002, for a similar approach). In most of the cases, the first three principal components are negatively correlated with the daily returns of all underlying stock indices. They also reflect, to some extent, movements of the Euro/USD exchange rate and the slope of the term structure of interest rates.

Next, the forecasting power of the principal components is tested with the regression of each volatility index on the lagged values of the first four principal components:

$$\Delta IV_t = c_1 + \sum_{j=1}^{2} r_{1j} PC1_{t-j} + \sum_{j=1}^{2} r_{2j} PC2_{t-j} + \sum_{j=1}^{2} r_{3j} PC3_{t-j} + \sum_{j=1}^{2} r_{4j} PC4_{t-j} \qquad (5)$$

where $r_{ij}, i = 1,...,4, j = 1,2$ are coefficients to be estimated. Table 6 shows the estimated coefficients and the Newey-West corrected *t*-statistics (within parenthesis). We can see that the fit of the model is rather poor for almost all volatility indices; the only exception occurs for the French VX1 and VX6 that exhibit an adjusted R^2 of 17% and 19%, respectively just as was the case with the economic variables model [equation (2)]. In general, all first four PCs explain the variability of the French indices.

6. Out-of-Sample Performance

We assess the out-of-sample performance of each one of the model specifications we have considered in the previous sections. This exercise is done for each implied volatility index. The models are compared with the random walk model that is used as a benchmark. In line with Gonçalves and Guidolin (2006), we use three metrics to assess the out-of-sample performance. In particular, the first metric is the root mean squared prediction error (RMSE) calculated as the square root of the average squared deviations of the actual value of the implied volatility index from the model's 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 value of the implied volatility index and the model's forecast, averaged over the number of observations. The third metric is the mean correct prediction (MCP) of the direction of change in the value of the implied volatility index calculated as the average frequency (percentage of observations) for which the change in the implied volatility index predicted by the model has the same sign as the realized change. The out-of-sample exercise is performed from 18/03/2005 to 8/01/2007 by increasing the sample size by one observation and re-estimating each model as time goes by.

Table 7 shows the results on the out-of-sample performance of the alternative model specifications for each one of the eight implied volatility indices. We can see that for any given metric and model, the differences in the performance of the model are very small across indices. This indicates that the various models compete very closely under the considered metrics. Most importantly, the more sophisticated models do not perform better than the random walk model. This is also manifested by the MCP criterion that is quite close to 50% across models and indices. Hence, the considered models do not have a superior performance compared with a naïve rule that "the predicted change in the implied volatility index has 50% chance to be positive and 50% to be negative". This comes at no surprise given that all specifications of the predictive regressions have a very poor fit within sample for all but the French implied volatility indices. Interestingly, the out-of-sample performance is poor for the French indices, as well.

7. Interval Forecasts: Statistical Evidence and Trading Game

7.1 Interval Forecasts: Construction

In Section 6 we found that the linear models do not perform better than the random walk model in an out-of-sample point forecast setting. Next, we construct interval forecasts for each one of the implied volatility indices from 18/03/2005 to 8/01/2007 by Historical Simulation (HS) and Monte Carlo (MC) simulation. The latter employs an alternative model to the ones that have been examined in the previous sections and found to perform poorly out-of-sample (see Chatfield, 1993, for a review on the construction of interval forecasts).

HS is based on the idea that the past is going to repeat itself in the future. This method is popular in a Value at Risk (VaR) setting (see e.g., Linsmeier and Pearson, 2000). The simulation is carried out for a one-day rolling window of sample size N=250 observations. To perform MC simulation, a stochastic process needs to be chosen; the process should account for the empirical regularities of the evolution of implied volatility indices. To this end, in line with the findings by Dotsis et al. (2007), we choose Merton's (1976) jump-diffusion (hereafter, GBMPJ). To fix ideas, GBMPJ is given by

$$dV_t = V_t \mu dt + \sigma V_t dW_t + (y-1)V_t dq_t \tag{6}$$

where V_t is the value of the implied volatility index at time t, dq is a Poisson process with constant arrival parameter λ (intensity), that is $\Pr\{dq_t=1\}=\lambda dt$, and $\Pr\{dq_t=0\}=1-\lambda dt$, and y is the jump amplitude. dW, dq and y are assumed to be mutually independent processes and the logarithm of the jump size y is assumed to be distributed normally with mean and variance γ and δ^2, respectively. The probability density function of the log-changes of the volatility index is known under the GBMPJ process (see Press, 1967). Hence, conditional maximum likelihood method is used to estimate the parameters of the model so as to capture the dependence of observations (see Dotsis et al., 2007, for a detailed description of the way that maximisation is carried out). The parameters of the process are re-estimated on each day, by adding to the initial sample the new observation that becomes available as time goes by[10]. The MC simulation is based on the solution of the GBMPJ so as to avoid

[10] Alternatively, we have also used a rolling window with constant sample size to estimate the parameters; the results were similar.

any discretisation error that would stem from using equation (6) per se. Every day, 10,000 simulation runs have been generated to construct the forecast intervals. Interval forecasts are formed out-of-sample by construction.

7.2 Interval Forecasts: Evaluating their Validity

To test the statistical efficacy of the forecast intervals, Christoffersen's (1998) likelihood ratio test of unconditional coverage is used; the test has been applied widely to backtest VaR models. The idea of the test is described as follows. A "good" α forecast interval is one for which the number of times that the actually realized value of the index falls outside the interval is α% of the times. Let an observed sample path $\{V_t\}_{t=1}^{T}$ of the time series of the index prices and a series of constructed interval forecasts $\{(L_{t/t-1}(a),\ U_{t/t-1}(a))\}_{t=1}^{T}$, where $L_{t/t-1}(a)$ and $U_{t/t-1}(a)$ are the lower and upper bounds of the forecast intervals for time t constructed at time t-1, respectively, corresponding to an interval of significance level (coverage probability) α. An indicator function I_t is defined, where

$$I_t = \begin{cases} 0, & \text{if } \mathrm{y_t} \in \left[L_{t/t-1}(a), U_{t/t-1}(a)\right] \\ 1, & \text{if } \mathrm{y_t} \notin \left[L_{t/t-1}(a), U_{t/t-1}(a)\right] \end{cases}$$

The null hypothesis H_0: $E(I_t) = \alpha$ is tested versus H_1: $E(I_t) \neq \alpha$. Under the null hypothesis, Christoffersen's test statistic is given by a likelihood ratio test.

Christoffersen's test is not model dependent, and therefore it can be applied to any assumed underlying stochastic process. On the other hand, the power of this test may be sensitive to the sample size. To overcome this constraint, we base the Accept/Reject decisions of the null hypothesis on MC simulated p-values. Table 8 shows the number and percentage (within parentheses) of observations that fall outside the constructed intervals, and the results from Christoffersen's (1998) test for the VIX and the VXD indices obtained by HS and MC simulation (Panels A and B, respectively) for 1% and 5% forecast intervals. We can see that the results are similar for the two indices for both significance levels. In particular, Christoffersen's test rejects the null hypothesis in almost all cases and for both methods. This implies that no accurate interval forecasts can be constructed for VIX/VXD using either HS or MC simulation.

7.3 Interval Forecasts: The Trading Game

A trading strategy with a single VIX and VXD volatility futures contract is constructed in order to evaluate the accuracy of the constructed interval forecasts under a financial metric. The trading game is used despite the fact that the interval forecasts have no predictive power from a statistical point of view. This is because the statistical evidence does not always corroborate a financial criterion (see also Ferson et al., 2003, p. 1395, for examples). The following trading rules are used:

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

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

Therefore, 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. The CBOE transaction costs are taken into account ($0.5 per transaction in one contract).

Table 9 and Table 10 show the cumulative Profit/Loss from the daily mark-to-market, the mean log-return, and the annualised Sharpe ratio obtained for the VIX and VXD futures (three shortest series), respectively. Results are reported for the interval forecasts derived by HS and MC simulation (Panels A and B, respectively) for significance levels a=1%, 5%. The results are also reported for the trading game based on Bollinger Bands (Panel C); the upper and lower bounds are constructed by adding/subtracting three 20-day standard deviations away from a 20-day moving average of the implied volatility index. To evaluate the statistical significance of the annualised Sharpe Ratio, 95% confidence intervals have been bootstrapped and reported within parenthesis. We can see that the annualized expected return and Sharpe Ratio are fairly small and insignificant for both the VIX and VXD futures[11]. Furthermore, the results are similar to those obtained under the Bollinger Bands, and they are comparable to the ones obtained for the market. The fact that no economically significant profits can be obtained is in accordance with the results from Christoffersen's test.

[11] The analysis has also been carried out by utilizing an alternative Sharpe Ratio based on semi-variance so as to account for the high kurtosis and skewness exhibited by the returns of the trading strategy. However, the results were in line with the ones presented in the paper.

8. Analysis over Monthly Horizons

For any given implied volatility index, we estimate the previously mentioned statistical models with monthly non-overlapping data to check whether there is evidence of predictability in monthly horizons; observations have been recorded on the first working day of each month. Non-overlapping data are used so as to avoid the problems in the statistical inference that are encountered in the case of long horizon predictive regressions with overlapping data (see e.g., Valkanov, 2003). In addition, the study of the dynamics of implied volatilities in longer horizons (say 2-4 years) is not of particular importance since most of the options' trading activity is focused on the shortest maturities. Due to space limitations, we only report the results from the predictive regression with the economic variables model [equation (2)] that has delivered the best results compared with the other specifications. The model has been estimated for the period 2/02/2001 to 17/03/2005, just as was the case with the daily data; 47 monthly observations have been used. Table 11 shows the estimated coefficients and the respective *t*-statistics within parentheses from regression (2) for each one of the eight implied volatility indices. We can see that there is evidence of predictability for VIX, VXOA, and VXD, as well as for VX1 and VX6; the R^2 ranges from 32% for VXOA to 20% for VX6. This is in contrast to the daily horizons where a predictable pattern was manifested only for the French indices. On the other hand, we find an almost zero R^2 for VXN, VDAX and VSTOXX just as was the case with the daily data. The predictive pattern seems to be attributed to only a few predictive variables. In particular, for VIX, VXOA and VXD we find that the positive returns and the exchange rate have a statistically significant negative effect on the implied volatility index, as expected. Finally, the coefficient of volume is significant and negatively signed for VX1 and VX6.

The statistical evidence of a more pronounced predictability in monthly horizons can be attributed either to the possible presence of mean reversion in the implied volatility indices or to the persistence of the implied volatility index relative to the persistence of its' predictors that appear in equation (2). We check both conjectures. We find that in the monthly horizons there is no evidence of mean reversion; the autoregressive coefficient in an AR(1) model for the changes in the implied volatility index is statistically insignificant. The increase in the R^2's seems to be explained by our second conjecture that is implied by the definition of R^2. Table 12 reports the ratio of the annualized standard deviation of the changes of each one of the eight implied volatility indices to its' corresponding predictors. The entries are shown for daily and monthly horizons (Panels A and B, respectively). We can see that in the cases where the R^2 has increased in the monthly horizons compared with the daily ones (i.e. VIX, VXOA and VXD), the ratios of volatilities of the statistically significant predictors (in bold) have decreased. This implies that the dependent variable has become more persistent compared with the persistence of its' predictors[12].

Next, we constructed out-of-sample point and interval forecasts with the models given by equations (2), (3), (4), and (5) for the period from 18/03/2005 to 8/01/2007; monthly forecasted values were generated by re-estimating the model as a new observation was becoming available. The out-of-sample performance of the alternative models is very close to the random walk model just as was the case with the daily horizons; this holds regardless of the volatility index under consideration. Then, the trading game with the VIX futures was performed just as in the case of the daily data; no trading game was performed for the VXD futures due to the lack of data once the filtering constraints were applied. We found that no economically significant profits can be generated; the annualized Sharpe ratios are again too small ranging from 0.2055 to 0.7054 (results are available from the authors upon request).

9. Conclusions

This paper has contributed to the literature of whether the evolution of implied volatility can be forecasted in the equity markets by using a plethora of European and U.S. implied volatility indices. To this end, a number of alternative model specifications have been examined to generate forecasts for both daily and monthly horizons. First, point forecasts were constructed. Parametric predictive regressions have been formed using economic variables and spillover effects (VAR model) as predictors, separately. A non-parametric specification using principal components was also tested. The performance of the various models was evaluated both in and out-of-sample. Next, interval forecasts were generated. Again, various models were used to this end. The accuracy of the interval forecasts was evaluated by statistical and economic criteria. The economic criterion was based on trading games with the VIX and VXD volatility futures.

Regarding the in-sample performance of the models, we found that the results depend on the horizon under consideration and the model specification. In the daily

[12] The first order autocorrelation coefficients of the monthly changes of each one of the economic variables is well below one (0.6 is the maximum value reported for the changes of the interest rate variable). Therefore, the results from the monthly horizon analysis do not suffer of the type of problems analysed by Ferson et al. (2003) and Torous et al. (2004), just as is the case with the daily horizons analysis.

horizons case, the majority of implied volatility indices cannot be predicted point-wise in a statistical sense; the only exception occurs for the French implied volatility indices where the VAR model performed marginally better among the competing specifications. In the monthly horizons case, the model with the economic variables as predictors performed best by providing fairly high R^2 for VIX, VXOA, VXD, and the French indices. On the other hand, the magnitude of predictability does not depend on the capitalization of the underlying stock index.

However, the out-of-sample statistical performance of the considered models is not superior to that of the random walk model. Furthermore, the constructed interval forecasts had no forecasting power either. In line with the statistical evidence, the trading games did not generate significant risk-adjusted profits once transaction costs were taken into account in both the daily and monthly horizons. These results indicate that the newly CBOE volatility futures markets are informational efficient just as other option markets. Given that the answer on the predictability question always depends on the assumed specification of the predictive regression, more complex model specifications should be considered. For instance, a model with time-varying coefficients where the predictors follow autoregressive processes could be examined. In the interests of brevity, this topic is best left for future research.

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Panel A: Implied Volatility Indices: 2/02/2001 to 17/03/2005– Summary Statistics (Levels)

	VIX	VXOA	VXN	VXD	VDAX	VX1	VX6	VSTOXX
Mean	0.22	0.20	0.37	0.21	0.27	0.23	0.22	0.28
Std. Deviation	0.07	0.07	0.14	0.07	0.10	0.09	0.06	0.11
Skewness	0.71	0.62	0.30	0.67	0.86	0.95	0.45	0.88
Kurtosis	2.83	2.62	1.89	2.64	2.81	3.16	2.99	2.90
Jarque – Bera	85*	70*	66*	79*	125*	152*	34*	129*
ρ_1	0.95*	0.96*	0.96*	0.96*	0.96*	0.94*	0.93*	0.97*
ADF	-2.07	-2.09	-2.71*	-1.64	-0.90	-0.99	-0.48	-1.12

Panel B: Implied Volatility Indices– Summary Statistics (Daily Differences)

	VIX	VXOA	VXN	VXD	VDAX	VX1	VX6	VSTOXX
Mean	-0.0004	-0.0004	-0.0010	-0.0004	-0.0005	-0.0005	-0.0004	-0.0005
Std. Deviation	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Skewness	0.21	0.17	-0.30	0.32	0.04	0.79	0.23	0.15
Kurtosis	4.90	5.92	6.20	6.93	5.05	17.02	12.75	6.33
Jarque – Bera	149*	338*	414*	620*	165*	7771*	3720*	436*
ρ_1	0.01	-0.03	0.05	0.02	0.00	-0.34*	-0.43*	-0.03
ADF	-30.89*	-31.98*	-29.16*	-30.39*	-31.95*	-20.32*	-28.05*	-24.52*

Panel C: Summary Statistics for VIX Futures: 18/03/2005 to 8/01/2007

	Levels			**Daily Differences**		
	Shortest	**Second Shortest**	**Third Shortest**	**Shortest**	**Second Shortest**	**Third Shortest**
# Observations	447	426	421			
Mean	134.46	143.20	150.91	0.00	0.00	0.00
Std. Deviation	14.41	117.72	10.40	0.03	0.02	0.02
Skewness	1.12	0.23	-0.10	0.15	1.17	0.30
Kurtosis	3.07	0.11	-0.19	16.16	7.01	6.67
ρ_1	0.94	0.95	0.95	0.020	0.033	-0.005
Average Volume	392.34	294.77	278.32			
(min-max)	*(5-6,091)*	*(5-4,683)*	*(5-4,564)*			

Panel D: Summary Statistics for VXD Futures

	Levels			**Daily Differences**		
	Shortest	**Second Shortest**	**Third Shortest**	**Shortest**	**Second Shortest**	**Third Shortest**
# Observations	337	253	209			
Mean	127.83	135.89	144.18	0.00	0.00	0.001
Std. Deviation	12.91	13.75	10.98	0.04	0.03	0.03
Skewness	1.27	0.51	0.36	0.03	0.36	-0.08
Kurtosis	2.70	-0.11	-0.01	9.49	4.69	7.82
ρ_1	0.93	0.92	0.91	0.003	0.031	-0.016
Average Volume	63.00	41.25	61.98			
(min-max)	*(5-319)*	*(5-308)*	*(5-2020)*			

Table 1: Summary Statistics. Entries report the descriptive statistics of the implied volatility indices in the levels and the first daily differences. The first order autocorrelations ρ_1, the Jarque-Bera and the Augmented Dickey Fuller (ADF) (no constant and trend have 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/ has a unit root, respectively. Summary statistics for the VIX and VXD futures in levels and changes are also provided.

	Dependent Variable: **ΔVIX$_t$**	Dependent Variable: **ΔVXOA$_t$**	Dependent Variable: **ΔVXN$_t$**	Dependent Variable: **ΔVXD$_t$**	Dependent Variable: **ΔVDAX$_t$**	Dependent Variable: **ΔVX1$_t$**	Dependent Variable: **ΔVX6$_t$**	Dependent Variable: **ΔVSTOXX$_t$**
Included Obs.	992	994	992	988	1024	1017	1028	1031
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
c_1	**-0.001***	**-0.001***	**-0.002***	**-0.001****	**-0.001***	**-0.002****	**-0.002****	**-0.002***
	(-3.142)	*(-3.450)*	*(-2.663)*	*(-2.362)*	*(-4.041)*	*(-2.007)*	*(-2.495)*	*(-3.184)*
R_t^+	**-0.728***	**-0.707***	**-0.343***	**-0.567***	**-0.456***	**-0.793***	**-0.596***	**-0.712***
	(-12.124)	*(-12.657)*	*(-7.417)*	*(-10.712)*	*(-9.813)*	*(-6.953)*	*(-6.469)*	*(-9.860)*
R_t^-	**-0.897***	**-0.858***	**-0.393***	**-0.681***	**-0.619***	**-1.035***	**-0.851***	**-0.911***
	(-17.583)	*(-19.230)*	*(-10.715)*	*(-12.330)*	*(-15.331)*	*(-6.466)*	*(-8.911)*	*(-12.651)*
i_t	0.002	-0.002	-0.040	-0.016	0.045	-0.021	0.009	0.000
	(0.154)	*(-0.180)*	*(-1.851)*	*(-1.188)*	*(1.208)*	*(-0.892)*	*(0.318)*	*(0.014*
fx_t	-0.009	-0.021	**-0.136****	-0.024	-0.047	-0.141	0.015	-0.013
	(-0.235)	*(-0.568)*	*(-2.154)*	*(-0.578)*	*(-0.942)*	*(-1.224)*	*(0.169)*	*(-0.197)*
oil_t	-0.021	-0.012	-0.016	-0.006	**-0.032***	-0.038	-0.002	-0.033
	(-1.802)	*(-0.855)*	*(0.783)*	*(-0.566)*	*(-2.632)*	*(-1.068)*	*(-0.072)*	*(-1.695)*
ΔHV_t	0.017	**0.079****	-0.009	-0.007	-0.009	0.328	0.108	0.169
	(0.404)	*(2.166)*	*(-0.303)*	*(-0.177)*	*(-0.119)*	*(1.331)*	*(0.968)*	*(1.596)*
Δys_t	0.000	-0.005	0.000	-0.007	0.005	-0.007	-0.013	0.010
	(-0.088)	*(-1.246)*	*(-0.033)*	*(-1.523)*	*(0.683)*	*(-0.496)*	*(-0.739)*	*(1.052)*
vol_t	**0.002***	-	0.002	0.001	**0.003***	0.001	0.000	**0.003***
	(2.674)	-	*(1.637)*	*(1.684)*	*(4.351)*	*(0.618)*	*(0.108)*	*(3.503)*
Adj.R-sq.	**0.638**	**0.676**	**0.354**	**0.506**	**0.587**	**0.324**	**0.318**	**0.616**
Residual Tests [p-values]								
Q(4)	0.01	0.32	0.05	0.00	0.00	0.00	0.00	0.00
ARCH(4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 2: Contemporaneous Relationship. The entries report results from the regression of each implied volatility index on a set of economic variables. The following specification is estimated $\Delta IV_t = c_1 + a_0^+ R_t^+ + a_0^- R_t^- + \beta_0 i_t + \gamma_0 fx_t + \delta_0 oil_t + \zeta_0 \Delta HV_t + \kappa_0 \Delta ys_t + \xi_0 vol_t + \varepsilon_t$, where ΔIV : the implied volatility index differenced, R^+ : the underlying stock index positive return, R^- : the underlying stock index negative return, *i*: the one-month interbank/Euribor interest rate for the US/European market, log-differenced, f_x: the EUR/USD exchange rate log-differenced, *oil*: WTI/Brent crude oil price for the American/European market, in log-differences, *HV*: historical volatility (a 30-day moving average of the past squared stock index returns) in differences, *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, the adjusted R^2 and the *p*-values that correspond to the residual diagnostics are reported. *Q*(4) is the *p*-value that corresponds to the *Q*-statistic for residual autocorrelation up to the order of 4 lags. The null hypothesis is that of no autocorrelation in the residuals up to the specified order. ARCH(4) is the *p*-value that corresponds to Engle's ARCH LM *t*-statistic. The null hypothesis is that of no heteroscedasticity in the residuals up to the specified order. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The model has been estimated for the period 2/02/2001 to 17/03/2005 over daily horizons.

	Dependent Variable: **ΔVIX_t**	Dependent Variable: **$\Delta VXOA_t$**	Dependent Variable: **ΔVXN_t**	Dependent Variable: **ΔVXD_t**	Dependent Variable: **$\Delta VDAX_t$**	Dependent Variable: **$\Delta VX1_t$**	Dependent Variable: **$\Delta VX6_t$**	Dependent Variable: **$\Delta VSTOXX_t$**
Included Obs.	954	955	953	950	1006	992	1008	1015
	Coeff. *(t-Statistic)*	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	-0.000	0.000	-0.001	0.002	0.002	0.000
	(0.475)	*(-0.462)*	*(-0.732)*	*(-0.364)*	*(-0.792)*	*(1.563)*	*(1.432)*	*(0.264)*
R_{t-1}^+	-0.023	0.001	-0.076	-0.104	-0.055	**-0.469***	-0.133	0.0002
	(-0.252)	*(0.006)*	*(-1.735)*	*(-1.620)*	*(-0.631)*	*(-3.701)*	*(-1.345)*	*(0.021)*
R_{t-1}^-	0.152	0.050	-0.008	-0.044	-0.126	-0.027	0.167	0.052
	(1.145)	*(0.404)*	*(-0.121)*	*(-0.426)*	*(-0.965)*	*(-0.189)*	*(1.302)*	*(0.416)*
i_{t-1}	-0.024	-0.020	**-0.041****	**-0.037***	-0.009	-0.133	**-0.058****	-0.016
	(-1.378)	*(-0.958)*	*(-2.576)*	*(-2.795)*	*(-0.320)*	*(-1.826)*	*(-2.281)*	*(-0.517)*
fx_{t-1}	-0.065	-0.064	-0.005	-0.041	0.072	0.222	0.054	0.180
	(-0.934)	*(-0.895)*	*(-0.050)*	*(-0.683)*	*(0.922)*	*(1.763)*	*(0.518)*	*(1.749)*
oil_{t-1}	0.022	-0.005	0.024	-0.007	0.005	-0.036	0.008	-0.018
	(1.356)	*(-0.307)*	*(1.203)*	*(-0.429)*	*(0.277)*	*(-1.040)*	*(0.340)*	*(-0.773)*
ΔHV_{t-1}	0.109	0.013	**0.092****	0.088	0.104	0.073	0.003	0.047
	(1.442)	*(0.181)*	*(2.136)*	*(1.491)*	*(1.260)*	*(0.478)*	*(0.019)*	*(0.464)*
ΔIV_{t-1}	0.067	-0.006	0.007	-0.042	-0.118	**-0.420***	**-0.420***	-0.004
	(0.701)	*(-0.062)*	*(0.136)*	*(-0.609)*	*(-0.868)*	*(-7.515)*	*(-5.721)*	*(-0.036)*
Δys_{t-1}	0.005	0.003	-0.001	0.000	-0.019	-0.007	-0.015	-0.012
	(0.838)	*(0.578)*	*(-0.083)*	*(0.005)*	*(-1.613)*	*(-0.307)*	*(-0.823)*	*(-0.669)*
vol_{t-1}	-0.001	-	0.001	0.001	0.000	-0.002	-0.001	0.000
	(-0.889)	-	*(0.569)*	*(0.561)*	*(0.128)*	*(-0.964)*	*(-0.953)*	*(-0.185)*
Adj.R-sq.	**0.004**	**-0.003**	**0.009**	**0.008**	**0.010**	**0.145**	**0.189**	**-0.003**
Residual Tests [p-values]								
Q(4)	0.00	0.01	0.13	0.01	0.09	0.00	0.00	0.129
ARCH(4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3: 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^+ : the underlying positive stock index return, R^- : the underlying negative stock index return, *i*: the one-month interbank/Euribor interest rate for the US/European market, log-differenced, f_x: the EUR/USD exchange rate log-differenced, *oil*: WTI/Brent crude oil price for the American/European market, in log-differences, *HV*: historical volatility (a 30-day moving average of the past squared stock index returns) in differences, *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, the adjusted R^2, and the *p*-values that correspond to the residual diagnostics are reported. *Q*(4) is the *p*-value that corresponds to the *Q*-statistic for residual autocorrelation up to the order of 4 lags. The null hypothesis is that of no autocorrelation in the residuals up to the specified order. ARCH(4) is the *p*-value that corresponds to Engle's ARCH LM *t*-statistic. The null hypothesis is that of no heteroscedasticity in the residuals up to the specified order. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The model has been estimated for the period 2/02/2001 to 17/03/2005 over daily horizons.

	Dependent Variable: ΔVIX_t	Dependent Variable: $\Delta VXOA_t$	Dependent Variable: ΔVXN_t	Dependent Variable: ΔVXD_t	Dependent Variable: $\Delta VDAX_t$	Dependent Variable: $\Delta VX1_t$	Dependent Variable: $\Delta VX6_t$	Dependent Variable: $\Delta VSTOXX_t$
Included Obs.	878	877	874	878	977	947	973	989
	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*	Coeff. *(t-Statistic)*
c_1	-0.001	-0.001	**-0.001***	-0.001	0.000	0.000	0.000	0.000
	(-1.865)	*(-1.957)*	*(-2.739)*	*(-1.596)*	*(-0.072)*	*(-0.254)*	*(-0.100)*	*(-0.181)*
ΔIV_{t-1}	-0.001	-0.035	0.040	0.017	0.006	**-0.390***	**-0.591***	-0.031
	(-0.019)	*(-0.656)*	*(0.961)*	*(0.364)*	*(0.122)*	*(-4.732)*	*(-8.456)*	*(-0.555)*
ΔIV_{t-2}	-0.087	-0.085	-0.058	**-0.082****	-0.026	**-0.257***	**-0.369***	-0.075
	(-1.928)	*(-1.702)*	*(-1.388)*	*(-2.320)*	*(-0.447)*	*(-3.997)*	*(-6.088)*	*(-1.769)*
ΔIV_{t-3}	**-0.084****	**-0.096****	-0.018	**-0.077****	-0.036	0.111	**-0.194***	0.011
	(-1.997)	*(-1.994)*	*(-0.532)*	*(-2.099)*	*(-0.951)*	*(1.157)*	*(-3.992)*	*(0.175)*
Adj.R-sq.	**0.012**	**0.014**	**0.002**	**0.010**	**-0.001**	**0.193**	**0.264**	**0.004**
Residual Tests [p-values]								
Q(4)	0.02	0.47	0.11	0.06	0.60	0.53	0.27	0.82
ARCH(4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 4: Forecasting with the Univariate Autoregressive model. The entries report results from the estimation of a univariate autoregressive model for the daily changes *ΔIV* of each implied volatility index. The specification $\Delta IV_t = c_1 + \sum_{j=1}^{3} \lambda_j \Delta IV_{t-j} + \varepsilon_t$ is used. The estimated coefficients, Newey-West *t*-statistics in parentheses, the adjusted R^2, and the *p*-values that correspond to the residual diagnostics are reported. *Q*(4) is the *p*-value that corresponds to the *Q*-statistic for residual autocorrelation up to the order of 4 lags. The null hypothesis is that of no autocorrelation in the residuals up to the specified order. ARCH(4) is the *p*-value that corresponds to Engle's ARCH LM *t*-statistic. The null hypothesis is that of no heteroscedasticity in the residuals up to the specified order. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The model has been estimated for the period 2/02/2001 to 17/03/2005 over daily horizons.

	Dependent Variable: **ΔVIX_t**	Dependent Variable: **$\Delta VXOA_t$**	Dependent Variable: **ΔVXN_t**	Dependent Variable: **ΔVXD_t**	Dependent Variable: **$\Delta VDAX_t$**	Dependent Variable: **$\Delta VX1_t$**	Dependent Variable: **$\Delta VX6_t$**	Dependent Variable: **$\Delta VSTOXX_t$**
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
ΔVIX_{t-1}	0.08	**0.46***	0.14	**0.35***	**0.33***	0.34	0.29	**0.31****
ΔVIX_{t-2}	0.01	**0.23****	0.10	0.16	0.17	0.02	-0.18	0.26
ΔVIX_{t-3}	-0.09	0.19	0.02	-0.11	-0.03	0.08	0.13	-0.12
$\Delta VXOA_{t-1}$	0.01	**-0.46***	-0.02	0.13	0.15	0.06	0.17	0.17
$\Delta VXOA_{t-2}$	0.10	**-0.20****	0.12	0.15	**0.21****	0.22	**0.31****	0.22
$\Delta VXOA_{t-3}$	0.14	**-0.19****	0.04	**0.17****	0.09	0.11	-0.09	0.06
ΔVXN_{t-1}	-0.06	-0.05	-0.09	-0.04	**-0.10****	-0.05	0.00	-0.03
ΔVXN_{t-2}	0.02	0.03	-0.09	0.00	-0.01	-0.04	0.02	-0.06
ΔVXN_{t-3}	-0.03	0.00	-0.06	0.01	-0.01	-0.10	0.01	0.00
ΔVXD_{t-1}	0.00	0.06	0.15	**-0.40***	-0.01	0.09	-0.14	0.00
ΔVXD_{t-2}	**-0.23***	-0.18	-0.23	**-0.37****	**-0.21***	0.00	0.00	**-0.27***
ΔVXD_{t-3}	-0.11	-0.10	0.01	-0.11	0.08	0.08	0.04	0.24
$\Delta VDAX_{t-1}$	-0.01	-0.01	0.07	-0.01	**-0.32***	-0.01	-0.12	0.11
$\Delta VDAX_{t-2}$	**-0.21***	**-0.19****	-0.04	-0.13	**-0.31***	-0.09	-0.20	-0.15
$\Delta VDAX_{t-3}$	-0.12	-0.12	-0.09	-0.03	**-0.18****	**-0.28****	-0.14	**-0.24****
$\Delta VX1_{t-1}$	0.03	0.03	0.00	0.03	0.02	**-0.53***	**0.10****	-0.01
$\Delta VX1_{t-2}$	-0.01	-0.01	0.00	0.00	-0.03	**-0.37***	-0.01	-0.04
$\Delta VX1_{t-3}$	0.02	0.03	0.02	0.02	0.03	-0.08	0.07	0.00
$\Delta VX6_{t-1}$	-0.03	-0.02	-0.02	-0.02	**-0.07****	0.02	**-0.75***	-0.08
$\Delta VX6_{t-2}$	0.02	0.01	-0.05	0.00	-0.04	-0.05	**-0.51***	-0.04
$\Delta VX6_{t-3}$	-0.02	-0.02	-0.07	-0.04	**-0.08****	**-0.14****	**-0.32***	-0.05
$\Delta VSTOXX_{t-1}$	-0.05	-0.03	-0.08	-0.03	0.10	0.17	0.09	**-0.25***
$\Delta VSTOXX_{t-2}$	**0.15****	**0.17***	0.09	**0.12****	**0.17***	**0.29***	**0.24***	0.02
$\Delta VSTOXX_{t-3}$	0.08	0.08	0.10	0.01	0.11	**0.24****	0.06	0.10
C	0.00	0.00	**-0.001****	0.00	0.00	0.00	0.00	0.00
Adj. R^2	**0.02**	**0.06**	**0.01**	**0.06**	**0.10**	**0.19**	**0.34**	**0.10**

Table 5: Forecasting with the VAR model. The entries report the estimated coefficients of a Vector Autoregression of the 3rd order, VAR(3), for the set of the eight Implied Volatility (IV) indices: $Y_t = C + \sum_{i=1}^{3} \Phi_i Y_{t-i} + u_t$, where $\boldsymbol{Y_t}$ is the (8x1) vector of IV indices (in differences), $\boldsymbol{C}$ is a (8x1) vector of constants, $\boldsymbol{\Phi_1}, \boldsymbol{\Phi_2}, \boldsymbol{\Phi_3}$ are (8x8) matrices of coefficients to be estimated, and u_t is a (8x1) vector of errors. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% levels, respectively, according to the computed *t*-statistics that are omitted due to space limitations. The model has been estimated for the period 2/02/2001 to 17/03/2005 over daily horizons.

	c	$PC1_{t-1}$	$PC1_{t-2}$	$PC2_{t-1}$	$PC2_{t-2}$	$PC3_{t-1}$	$PC3_{t-2}$	$PC4_{t-1}$	$PC4_{t-2}$	Adj. R^2
ΔVIX_t	-0.0003	-0.0002	-0.0009	0.0001	0.0006	0.0007	0.0007	0	-0.0005	0.0075
	(-0.6897)	(-0.4372)	(-1.6833)	(-0.0958)	(-1.2587)	(-1.3147)	(-1.3972)	(-0.0771)	(-0.9001)	
$\Delta VXOA_t$	-0.0003	-0.0002	-0.0008	0.0002	0.0006	0.0005	0.0005	0.0006	-0.0002	0.0046
	(-0.7851)	(-0.3008)	(-1.6024)	(-0.4013)	(-1.3503)	(-0.8769)	(-0.8198)	(-0.8192)	(-0.4279)	
ΔVXN_t	-0.0009	0.0015*	0.0001	-0.0006	0.0003	0.0005	-0.0001	-0.0009	-0.0011	0.0109
	(-1.9376)	(-2.8083)	(-0.1368)	(-1.0050)	(-0.5746)	(-0.9314)	(-0.1514)	(-1.1177)	(-1.7036)	
ΔVXD_t	-0.0003	0.0007	-0.0002	-0.0001	0.0005	**0.0010****	0.0003	-0.0003	-0.0007	0.0099
	(-0.8790)	(-1.5739)	(-0.5293)	(-0.3634)	(-1.1767)	(-2.3514)	(-0.8544)	(-0.6033)	(-1.1534)	
$\Delta VDAX_t$	-0.0002	**0.0017***	0.0004	**-0.0019***	-0.0009	**0.0014****	0.0009	-0.0004	-0.001	0.0527
	(-0.5858)	(-3.5043)	(-0.7451)	(-4.0327)	(-1.5764)	(-2.3888)	(-1.6656)	(-0.5701)	(-1.6815)	
$\Delta VX1_t$	-0.0001	0	0.0005	**-0.0083***	**-0.0050***	**-0.0025****	**-0.0024****	**-0.0066***	**-0.0030***	0.1672
	(-0.1461)	(-0.0185)	(-0.5702)	(-6.7928)	(-6.0048)	(-1.9671)	(-2.5458)	(-6.0580)	(-3.5611)	
$\Delta VX6_t$	0.0002	-0.0023*	**-0.0016****	**-0.0076***	**-0.0037***	**-0.0046***	**-0.0024****	**0.0030****	-0.0004	0.1902
	(-0.3961)	(-3.2205)	(-2.3964)	(-6.4991)	(-4.0216)	(-3.5532)	(-2.3315)	(-2.2809)	(-0.4061)	
$\Delta VSTOXX_t$	0	**0.0021***	0.0006	**-0.0029***	-0.0011	0.0014	0.0013	-0.0011	**-0.0014****	0.0516
	(-0.0843)	(-3.2082)	(-0.7814)	(-4.5740)	(-1.5821)	(-1.693)	(-1.808)	(-1.1681)	(-2.0418)	

Table 6: Forecasting with the Principal Components Analysis Model. The entries report results from the regression $\Delta IV_t = c_1 + \sum_{j=1}^{2} r_{1j} PC1_{t-j} + \sum_{j=1}^{2} r_{2j} PC2_{t-j} + \sum_{j=1}^{2} r_{3j} PC3_{t-j} + \sum_{j=1}^{2} r_{4j} PC4_{t-j}$ of the changes ΔIV of each implied volatility index on the lagged first four principal components PC1, PC2, PC3 and PC4 derived from the set of the eight IV indices. The estimated coefficients, t-statistics in parentheses, and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The model has been estimated for the period 2/02/2001 to 17/03/2005 over daily horizons.

Panel A: Random Walk								
	VIX	VXOA	VXN	VXD	VDAX	VX1	VX6	VSTOXX
RMSE	0.0081	0.0086	0.0084	0.0077	0.0076	0.0168	0.0049	0.0083
MAE	0.0054	0.0058	0.0059	0.0050	0.0053	0.0096	0.0035	0.0059
MCP	NA	NA	NA	NA	NA	NA	NA	NA

Panel B: Regression Model Based on Economic Variables								
	VIX	VXOA	VXN	VXD	VDAX	VX1	VX6	VSTOXX
RMSE	0.0081	0.0073	0.0084	0.0073	0.0077	0.0156	0.0053	0.0084
MAE	0.0053	0.0049	0.0059	0.0049	0.0054	0.0156	0.0038	0.0060
MCP	0.5508	0.5343	0.5414	0.5177	0.5246	0.5591	0.5224	0.4922

Panel C: AR(3) Model								
	VIX	VXOA	VXN	VXD	VDAX	VX1	VX6	VSTOXX
RMSE	0.0080	0.0085	0.0083	0.0073	0.0077	0.0160	0.0056	0.0084
MAE	0.0052	0.0056	0.0059	0.0048	0.0053	0.0098	0.0041	0.0060
MCP	0.5371	0.5345	0.5601	0.5345	0.5402	0.5594	0.5358	0.5114

Panel D: VAR Model								
	VIX	VXOA	VXN	VXD	VDAX	VX1	VX6	VSTOXX
RMSE	0.0085	0.0090	0.0087	0.0079	0.0087	0.0210	0.0067	0.0092
MAE	0.0055	0.0060	0.0061	0.0052	0.0060	0.0121	0.0047	0.0064
MCP	0.5189	0.5283	0.5786	0.5220	0.4985	0.4644	0.4867	0.5134

Panel E: PCA Regression Model								
	VIX	VXOA	VXN	VXD	VDAX	VX1	VX6	VSTOXX
RMSE	0.0082	0.0108	0.0460	0.0093	0.0279	0.0360	0.0344	0.0324
MAE	0.0053	0.0083	0.0426	0.0077	0.0245	0.0286	0.0271	0.0284
MCP	0.4816	0.4901	0.5581	0.4816	0.5344	0.5944	0.5470	0.5565

Table 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. RMSE is calculated as the square root of the average squared deviations of the actual value of the implied volatility index from the model's forecast, averaged over the number of observations. MAE is calculated as the average of the absolute differences between the actual value of the implied volatility index and the model's forecast, averaged over the number of observations. MCP is calculated as the average frequency (percentage of observations) for which the change in the implied volatility index predicted by the model has the same sign as the realized change. The Random Walk model (Panel A), the Regression model based on economic variables (Panel B), an AR(3) Model (Panel C), the VAR model (Panel D), and the PCA regression model (Panel E) have been implemented. The models have been estimated recursively for the period 18/03/2005 to 8/01/2007 over daily horizons.

Panel A: Historical Simulation Interval Forecasts				
	VIX		**VXD**	
Forecast Interval	**1%**	**5%**	**1%**	**5%**
# Violations	11	31	10	27
	(2.42%)	*(6.81%)*	*(2.20%)*	*(5.93%)*
*LR*unc	6.61	2.84	4.92	0.79
p-value	*(0.0180)*	*(0.1111)*	*(0.0163)*	*(0.3902)*
Decision	***Reject***	***Accept***	***Reject***	***Accept***
Panel B: Monte Carlo Interval Forecasts				
	VIX		**VXD**	
Forecast Interval	**1%**	**5%**	**1%**	**5%**
# Violations	18	34	13	37
	(3.30%)	*(7.47%)*	*(2.86%)*	*(8.13%)*
*LR*unc	15.13	5.12	10.55	7.97
p-value	*(0.0001)*	*(0.0259)*	*(0.0007)*	*(0.0034)*
Decision	***Reject***	***Reject***	***Reject***	***Reject***

Table 8: Statistical Accuracy of the Interval Forecasts. Entries report the number and percentage (within parentheses) of the observations that fall outside the constructed intervals, and the results from Christoffersen's (1998) likelihood ratio test LR_{unc} of unconditional coverage for VIX and VXD from 18/03/2005 to 8/01/2007 for two alternative significance levels (*a*=1% and *a*=5%). The results are reported for daily interval forecasts generated by Historical Simulation using a sample size of *N*=250 observations (Panel A) and by Monte Carlo (MC) simulation (Panel B). To generate the MC forecast intervals, the Geometric Brownian Motion with Jumps (GBMPJ) process $dV_t = V_t \mu dt + \sigma V_t dW_t + (y-1)V_t dq_t$ is used with jump size *y*, $\ln y \sim N(\gamma, \delta)$, and $E(dq)=\lambda dt$ where *dq* is the standard Poisson counter for the occurrence of jumps. In particular, the solution of the GBMPJ $\left(V_{t+dt} = Vt \exp\left[\left(\mu - \sigma^2/2\right)dt + \sigma(W_{t+dt} - W_t) + dq \ln y\right]\right)$ has been employed to this end.

Panel A: Historical Simulation Interval Forecasts						
	Shortest		2nd Shortest		3rd Shortest	
Forecast Interval	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
Profit/Loss	-8,033	-6,681	-173	699	-473	-2,201
Mean Return	-0.3105	-0.2680	0.0132	0.0180	-0.0072	-0.1015
Sharpe Ratio	-0.5748	-0.4954	0.0336	0.0457	-0.0210	-0.2967
95% CI	*(-2.09, 0.90)*	*(-2.05, 0.97)*	*(-1.56, 1.52)*	*(-1.58, 1.52)*	*(-1.63, 1.52)*	*(-1.87, 1.27)*

Panel B: Monte Carlo Interval Forecasts						
	Shortest		2nd Shortest		3rd Shortest	
Forecast Interval	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
Profit/Loss	-1,811	-1,811	4,309	4,309	2,089	2,089
Mean Return	-0.0795	-0.0795	0.1907	0.1907	0.0893	0.0893
Sharpe Ratio	-0.1470	-0.1470	0.4849	0.4849	0.2621	0.2621
95% CI	*(-1.69, 1.33)*	*(-1.66, 1.34)*	*(-1.11, 1.98)*	*(-1.11, 1.97)*	*(-1.33, 1.84)*	*(-1.33, 1.84)*

Panel C: Bollinger Bands			
	Shortest	**2nd Shortest**	**3rd Shortest**
Profit/Loss	5,899	3,819	4,459
Mean Return	0.2677	0.1443	0.1955
Sharpe Ratio	0.4919	0.3642	0.5699
95% CI	*(-1.06, 1.84)*	*(-1.23, 1.82)*	*(-1.05, 2.09)*

Table 9: Trading Game with the VIX futures from 18/03/2005 to 8/01/2007. The total net profit/loss, the average annualized log-return, the annualized Sharpe Ratio and the corresponding bootstrapped 95% confidence intervals (CI) are reported. For comparison, the market proxy (S&P 500) has a mean return of 0.0915 and a Sharpe Ratio of 0.9221 [*95% CI* = (-0.50, 2.36)]. **Panel A:** The entries show the results from the trading game based on the Historical Simulation interval forecasts. Results are reported a sample size of *N*=250 observations and two significance levels (*a*=1% and *a*=5%). **Panel B:** The entries show the results from the trading game based on the Monte Carlo interval forecasts. To estimate the Monte Carlo Forecast intervals, the solution of the GBMPJ $\left(V_{t+dt} = Vt\exp\left[\left(\mu - \sigma^2/2\right)dt + \sigma\left(W_{t+dt} - W_t\right) + dq\ln y\right]\right)$ has been used. Results are reported for two alternative significance levels (*a*=1% and *a*=5%). **Panel C:** The entries shows the results from the trading game based on Bollinger Bands.

	Panel A: Historical Simulation Interval Forecasts					
	Shortest		**2nd Shortest**		**3rd Shortest**	
Forecast Interval	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
Profit/Loss	-4,343	-2,463	1,026	2,127	-2,373	4,107
Mean Return	-0.2886	-0.1671	0.1188	0.2133	-0.2837	0.5401
Sharpe Ratio	-0.4138	-0.2399	0.2320	0.4167	-0.6797	1.2976
95% CI	*(-2.15, 1.50)*	*(-2.13, 1.54)*	*(-2.05, 2.64)*	*(-1.97, 2.75)*	*(-3.33, 1.95)*	*(-1.31, 3.98)*
	Panel B: Monte Carlo Interval Forecasts					
Forecast Interval	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
Profit/Loss	79	79	1,889	1,889	2,209	2,209
Mean Return	0.0232	0.0232	0.0007	0.0007	0.2720	0.2720
Ann Sharpe Ratio	0.0334	0.0334	0.3428	0.3428	0.6519	0.6519
Ann 95% CI	*(-1.86, 1.86)*	*(-1.82, 1.92)*	*(-2.04, 2.67)*	*(-2.06, 2.66)*	*(-1.94, 3.33)*	*(-2.00, 3.35)*

	Panel C: Bollinger Bands		
	Shortest	**2nd Shortest**	**3rd Shortest**
Profit/Loss	-983	-4,013	1,368
Mean Return	-0.0108	-0.3435	0.2486
Ann Sharpe Ratio	-0.0155	-0.6753	0.5876
Ann 95% CI	*(-2.02, 1.74)*	*(-3.22, 1.63)*	*(-2.20, 3.09)*

Table 10 Trading Game with the VXD futures from 18/03/2005 to 8/01/2007. The total net profit/loss, the average annualized log-return, the annualized Sharpe Ratio and the corresponding bootstrapped 95% confidence intervals (CI) are reported. For comparison, the market proxy (Dow Jones Industrial Average) has a mean return of 0.0834 and a Sharpe Ratio of 0.8431 [*95% CI* = (-0.56, 2.29)]. **Panel A:** The entries show the results from the trading game based on the Historical Simulation interval forecasts. Results are reported a sample size of N=250 observations and two significance levels (a=1% and a=5%). **Panel B:** The entries show the results from the trading game based on the Monte Carlo interval forecasts. To estimate the Monte Carlo Forecast intervals, the solution of the GBMPJ $\left(V_{t+dt} = Vt\exp\left[\left(\mu - \sigma^2/2\right)dt + \sigma\left(W_{t+dt} - W_t\right) + dq\ln y\right]\right)$ has been used. Results are reported for two alternative significance levels (a=1% and a=5%). **Panel C:** The entries shows the results from the trading game based on Bollinger Bands.

	ΔVIX	ΔVXOA	ΔVXN	ΔVXD	ΔVDAX	ΔVX1	ΔVX6	ΔVSTOXX
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(t-Stat.)	(t-Stat.)	(t-Stat.)	(t-Stat.)	(t-Stat.)	(t-Stat.)	(t-Stat.)	(t-Stat.)
c_1	-0.010	-0.007	-0.011	-0.002	-0.013	-0.016	-0.012	-0.020
	(-1.102)	(-1.028)	(-0.812)	(-0.316)	(-0.785)	(-1.108)	(-1.433)	(-0.886)
R_{t-1}^{+}	**-0.640****	**-0.765***	-0.404	**-0.548****	-0.429	-0.499	-0.195	-0.119
	(-2.053)	(-4.729)	(-1.074)	(-2.199)	(-1.231)	(-1.007)	(-0.892)	(-0.229)
R_{t-1}^{-}	-0.470	-0.389	-0.302	-0.217	-0.434	-0.498	-0.322	-0.358
	(-1.772)	(-1.197)	(-0.907)	(-0.847)	(-1.272)	(-1.517)	(-1.529)	(-0.834)
i_{t-1}	0.019	0.005	0.068	0.003	-0.052	-0.017	-0.007	-0.029
	(0.599)	(0.238)	(1.375)	(0.101)	(-0.606)	(-0.215)	(-0.171)	(-0.278)
fx_{t-1}	**-0.733***	**-0.660***	-0.549	**-0.468****	-0.425	-0.691	-0.235	-0.486
	(-3.573)	(-2.888)	(-1.907)	(-2.581)	(-1.379)	(-1.812)	(-0.876)	(-1.281)
oil_{t-1}	0.055	**0.077****	-0.044	0.081	0.102	0.126	0.070	0.141
	(1.051)	(2.493)	(-0.578)	(1.637)	(1.155)	(1.532)	(1.779)	(1.282)
ΔHV_{t-1}	-0.317	0.173	0.050	0.755	-1.357	-1.524	-1.379	-1.667
	(-0.261)	(0.183)	(0.088)	(0.751)	(-1.141)	(-1.092)	(-1.497)	(-1.208)
ΔIV_{t-1}	**-0.505****	**-0.626***	-0.130	-0.246	-0.454	-0.161	-0.043	-0.153
	(-2.150)	(-4.020)	(-0.658)	(-1.142)	(-1.350)	(-0.580)	(-0.212)	(-0.482)
Δys_{t-1}	0.023	0.014	0.024	0.011	0.000	-0.002	0.007	0.011
	(1.274)	(1.444)	(0.912)	(0.653)	(0.004)	(-0.063)	(0.340)	(0.206)
vol_{t-1}	-0.005	-	-0.011	-0.011	-0.056	**-0.164****	**-0.089****	-0.033
	(-0.561)	-	(-0.510)	(-0.720)	(-1.491)	(-2.431)	(-2.496)	(-1.019)
Adj.R-sq	**0.21**	**0.32**	**0.00**	**0.21**	**0.04**	**0.28**	**0.20**	**-0.03**
Residual tests (p-values reported)								
Q(4)	0.27	0.21	0.09	0.83	0.12	0.04	0.01	0.11
ARCH(4)	0.49	0.03	0.28	0.51	0.83	0.01	0.17	0.54

Table 11: Forecasting over Monthly Horizons. 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^{+}: the underlying positive stock index return, R^{-}: the underlying negative stock index return, i: the one-month interbank/Euribor interest rate for the US/European market, log-differenced, f_x: the EUR/USD exchange rate log-differenced, *oil*: WTI/Brent crude oil price for the American/European market, in log-differences, *HV*: historical volatility (a 30-day moving average of the past squared stock index returns) in differences, 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, the adjusted R^2, and the *p*-values that correspond to the residual diagnostics are reported. *Q*(4) is the *p*-value that corresponds to the *Q*-statistic for residual autocorrelation up to the order of 4 lags. The null hypothesis is that of no autocorrelation in the residuals up to the specified order. ARCH(4) is the *p*-value that corresponds to Engle's ARCH LM *t*-statistic. The null hypothesis is that of no heteroscedasticity in the residuals up to the specified order. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The model has been estimated for the period 2/02/2001 to 17/03/2005 over daily horizons.

Panel A: Ratio of Annualised Standard Deviations over Daily Horizons

	$\Delta IV_t/R_{t-1}^+$	$\Delta IV_t/R_{t-1}^-$	$\Delta IV_t/i_{t-1}$	$\Delta IV_t/fx_{t-1}$	$\Delta IV_t/oil_{t-1}$	$\Delta IV_t/\Delta HV_{t-1}$	$\Delta IV_t/\Delta IV_{t-1}$	$\Delta IV_t/\Delta ys_{t-1}$	$\Delta IV_t/vol_{t-1}$
ΔVIX	**1.68**	1.69	0.44	**1.95**	0.52	1.71	1.00	0.17	0.04
ΔVXOA	**1.58**	1.58	0.44	**1.94**	0.52	1.58	1.00	0.17	
ΔVXN	1.06	1.04	0.52	2.29	0.61	1.05	1.00	0.20	0.04
ΔVXD	**1.45**	1.48	0.38	**1.69**	0.45	1.33	1.00	0.03	0.15
ΔVDAX	1.21	1.16	0.61	2.15	0.57	1.29	1.00	0.29	0.04
ΔVX1	2.87	2.79	1.27	4.46	1.19	2.97	1.00	0.59	0.06
ΔVX6	2.23	2.17	0.98	3.47	0.93	2.31	1.00	0.46	0.04
ΔVSTOXX	1.78	1.73	0.83	2.91	0.78	1.94	1.00	0.39	0.05

Panel B: Ratio of Annualised Standard Deviations over Monthly Horizons

	$\Delta IV_t/R_{t-1}^+$	$\Delta IV_t/R_{t-1}^-$	$\Delta IV_t/i_{t-1}$	$\Delta IV_t/fx_{t-1}$	$\Delta IV_t/oil_{t-1}$	$\Delta IV_t/\Delta HV_{t-1}$	$\Delta IV_t/\Delta IV_{t-1}$	$\Delta IV_t/\Delta ys_{t-1}$	$\Delta IV_t/vol_{t-1}$
ΔVIX	**1.46**	1.10	0.13	**1.19**	0.37	7.44	0.99	0.09	0.06
ΔVXOA	**1.34**	1.04	0.13	**1.17**	0.36	6.95	0.99	0.08	
ΔVXN	0.82	0.60	0.17	1.53	0.47	2.95	0.99	0.11	0.13
ΔVXD	**1.33**	1.16	0.13	**1.15**	0.35	6.39	0.99	0.08	0.10
ΔVDAX	0.95	1.38	0.47	1.94	0.52	4.71	0.99	0.26	0.19
ΔVX1	2.20	1.47	0.56	2.30	0.62	6.37	0.99	0.31	0.32
ΔVX6	1.26	0.84	0.32	1.32	0.36	3.65	0.99	0.18	0.18
ΔVSTOXX	2.14	1.38	0.56	2.28	0.61	5.98	0.99	0.31	0.15

Table 12: Persistence of the Dependent Variables and Predictors. The entries report the ratio of the annualised standard deviation of the changes ΔIV of the implied volatility index to each one the economic variables, where: R^+: the underlying positive stock index return, R^-: the underlying negative stock index return, i: the one-month interbank/Euribor interest rate for the US/European market, log-differenced, f_x: the EUR/USD exchange rate log-differenced, *oil*: WTI/Brent crude oil price for the American/European market, in log-differences, ΔHV: changes of the historical volatility (a 30-day moving average of the past squared stock index returns), 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. Results are reported for the daily and monthly frequency (Panels A and B, respectively) and each one of the eight implied volatility indices (VIX, VXOA, VXN, VXD, VDAX, VX1, VX6, VSTOXX). The annualised standard deviations have been estimated for the period 2/02/2001 to 17/03/2005.