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

Eirini Konstantinidi[a], George Skiadopoulos[b **], Emilia Tzagkaraki[a]

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Abstract

We address the question whether the evolution of implied volatility can be forecasted by studying a number of European and U.S. implied volatility indices. 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.

JEL Classification: C53, G10, G12, G13, G14.

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

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[a] Department of Banking and Financial Management, University of Piraeus, ekonst@webmail.unipi.gr, etzagk@unipi.gr

[b] Corresponding author. Department of Banking and Financial Management, University of Piraeus, and Financial Options Research Centre, Warwick Business School, University of Warwick, gskiado@unipi.gr

** Postal Address: University of Piraeus, Department of Banking and Financial Management, Karaoli and Dimitriou 80, Piraeus 18534, Greece, Tel: +30-210-4142363.

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]. 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, and the references therein). 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 (i.e., whether abnormal profits can be made).

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 volatilities across option strike prices and expiry dates (implied volatility 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. 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. 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 Oozeer (2002) have addressed this question in the S&P 100, Philadelphia

[1] This question is distinct from the question whether implied volatility can forecast the future realised volatility. 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 a review).

Stock Exchange currency, and LIFFE long gilt futures options markets, respectively. To this end, they used sets of economic variables 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 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 (see also Han, 2007, for a similar approach in the setting of stock return predictability). Finally, the economic significance of the statistical evidence is assessed by means of trading strategies in the newly introduced and fast growing Chicago Board Options Exchange (CBOE) volatility futures markets. The results will have implications about the efficiency of these markets that has not yet been investigated, 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 implied 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 (see Dotsis et al., 2007, for a review of the literature). In addition, they affect the pricing of variance and volatility swaps (see e.g., Chriss and Morokoff, 1999)[2]. Furthermore, the implied volatility index can also be used for Value-at-Risk purposes (Giot, 2005a), to identify profitable opportunities in the stock market (Giot, 2005b, Banerjee et al., 2007), and to forecast the future market volatility (see e.g., Moraux et al., 1999, Simon, 2003, Giot, 2005a, Becker et al., 2007 among others).

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), Ahoniemi (2006), 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 performing 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. The last Section concludes and the implications of the research are outlined.

[2] A variance swap is actually a forward contract where the buyer (seller) 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). The volatility swap is defined similarly; a volatility rather than a variance index serves as the underlying asset.

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 and three European implied volatility indices are examined: VIX, VXO, VXN, VXD, VDAX-New, VCAC, 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-New is constructed from the implied volatilities of options on DAX (Germany), while VCAC is 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-New and VCAC are obtained from Bloomberg while for the other indices are obtained from the websites of the corresponding exchanges. All indices but VXO are constructed by the VIX algorithm (see the CBOE VIX white paper, and Carr and Wu, 2006, for a description of the VXO algorithm)[3]. 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 (see e.g., Carr and Wu, 2006, and the references therein). 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 remaining indices represent the 30-day variance swap rate of a variance swap once they are squared (see Carr and Wu, 2006).

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

The set of economic variables consists of the corresponding underlying to the options stock indices, two one-month interbank interest rates, the USD Libor (Euribor) rates, r^{US} (r^{EU}), the exchange rate $fx^{€/\$}$ of Euro/USD, the prices O^{WTI} (O^{BRENT}) of the WTI (Brent) crude oil, 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[4].

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[5]. 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 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 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 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. Interestingly, 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 that the VXD ones, as expected.

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

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

3. The 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, 2006, for a similar approach). In particular, the following general forecasting specification is employed:

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

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 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 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., Goyal and Welch, 2007, and the references therein). 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). The historical volatility is calculated as a 30-day moving average of equally weighted past squared returns. Furthermore, the above mentioned set of economic variables is augmented by adding the changes of historical volatility and the term ΔIV_{t-1} as explanatory variables; Harvey and Whaley (1992) and Guo (2000) have found the latter term to be statistically significant for the purposes of predicting implied volatility.

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. One lag is used since this is found to minimise the BIC criterion (within a range up to ten lags). For any given implied volatility index, the predictive regressions have the form:

$$\Delta IV_t = c_1 + \sum_{j=1}^{1} \lambda_j \Delta IV_{t-j} + \varepsilon_t \quad (2)$$

The VAR specification is given by

$$Y_t = C + \Phi_1 Y_{t-1} + \varepsilon_t \quad (3)$$

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 (1), (2), and (3) where the set of forecasting variables was chosen a priori.

For the purposes of our analysis, the PCs are used as forecasting variables in a regression setting where the dependent variable is a given implied volatility index. First, we apply PCA to the daily changes of implied volatility indices. The first four PCs are retained. These explain 94% 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 the economic variables model [equation (1)] are calculated (see also Mixon, 2002, for a similar approach). Strong correlations appear only in the case of the first two PCs with the returns of the underlying stock indices (Tables are available from the authors upon request). Next, each volatility index is regressed on the previous day values of the first four PCs (PCA model) to assess the forecasting power of the principal components, i.e.:

$$\Delta IV_t = c_1 + r_1 PC1_{t-1} + r_2 PC2_{t-1} + r_3 PC3_{t-1} + r_4 PC4_{t-1} + \varepsilon_t \tag{4}$$

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

$$\Phi(L)\Delta^d IV_t = c + \Theta(L)\varepsilon_t \tag{5}$$

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. It is assumed that $\Phi(L)$ and $\Theta(L)$ have no common roots and that their roots lie outside the unit circle. The ARFIMA(*p*,*d*,*q*) model is defined by

$$\Phi(L)(1-L)^d(\Delta IV_t - \mu) = \Theta(L)\varepsilon_t \tag{6}$$

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 in the frequency domain is performed 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

$$E\left(IV_{t+1} \middle| I_t\right) = IV_t + \mu - \sum_{j=1}^{\infty} \pi_j \left(\Delta IV_{t-j+1} - \mu\right) \tag{7}$$

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 (7), the infinite summation is truncated at k = 150.

4. In-Sample Evidence

Tables 2, 3, 4, and 5 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] 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. Harvey and Whaley (1992) had also found that interest rate variables and the lagged index returns couldn't predict the future changes in the implied volatility of the S&P 100 options. Brooks (1998) had also found that the volume couldn't 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. 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, 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).

Table 3 (Panel A) shows the results from the AR(1) model [equation (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 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 4 shows the results from the PCA model [equation (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 5 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 among the considered models. 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 (e.g., spillover effects) 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 one of the model specifications we have considered in Section 4. The out-of-sample exercise is performed from March 17, 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. 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 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. The null hypothesis is that the random walk model and the model under consideration perform equally well[6].

Table 6 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% (15/72) 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

[6] 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%.

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 is used. A "good" *α%* interval forecast is one for which the number of times that the realized value of the volatility index falls outside the interval is *α*% of the times. To fix ideas, let an observed sample path $\{IV_t\}_{t=1}^{T}$ of the time series of the implied volatility index and a series of constructed interval forecasts $\{(L_{t/t-1}(\alpha),\ U_{t/t-1}(\alpha))\}_{t=1}^{T}$, where $L_{t/t-1}(\alpha)$ and $U_{t/t-1}(\alpha)$ are the lower and upper bounds of the interval forecasts for time *t* constructed at time *t*-1, respectively, corresponding to an interval of significance level *α*. An indicator function I_t is defined, where

$$I_t = \begin{cases} 0, & \text{if } \mathrm{IV_t} \in \left[L_{t/t-1}(\alpha), U_{t/t-1}(\alpha)\right] \\ 1, & \text{if } \mathrm{IV_t} \notin \left[L_{t/t-1}(\alpha), U_{t/t-1}(\alpha)\right] \end{cases} \tag{8}$$

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. Therefore, we base the accept/reject decisions of the null hypothesis on MC simulated *p*-values. Table 7 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 the ARFIMA(1,*d*,1) models (Panels A, B, C, D, E, and F, respectively) for each one of the seven implied volatility indices. 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 47% 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. This is stronger for the U.S. indices; this is in contrast to the point forecasts case where the 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. They 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, p. 1395, for examples). The CBOE transaction costs are taken into account (\$0.5 per transaction in one 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 8 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[7]. 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

[7] A_p is used since the distribution of the returns of the futures trading strategy is non-normal (results are not reported due to space limitations). 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.

significance. We can see that *SR* and A_p are statistically insignificant in almost all cases; the only exceptions occur for the VXD shortest futures under the AR(1) and PCA models. 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 [see equation (8)][8].

Table 9 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[9].

[8] 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 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.

[9] The robustness of the reported results (statistical and economic significance of point and interval forecasts) across various sub-periods was 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,

7. 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 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 model) 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; the trading games did not generate significant risk-adjusted profits.

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 and criteria for choosing them should be considered (see e.g., Gonçalves and Guidolin, 2006, and Pesaran and Timmermann, 1995, respectively). Also longer horizons can be examined. In the interests of brevity, these topics are best left for future research.

2005 was used to form forecasts for the observations over the next 100 observations (first out-of-sample period). Then, we added these 100 observations to the initial sample and generated forecasts for the next 100 observations (second out-of-sample period). The new augmented sample was used to generate forecasts for the next 100 observations and so forth. Overall, six out-of-sample periods were formed. All models are re-estimated at each time step (i.e. daily). We found that the reported results were not sensitive to the period under consideration. Another robustness check was conducted by implementing the trading strategies without taking into account the CBOE transaction costs. Again, the reported results were not affected.

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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
Jarque – Bera	97*	81*	68*	86*	128*	199*	144*
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
Jarque – Bera	218*	381*	386*	654*	2,512*	8,329*	10,123*
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 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) (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/ 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: $\Delta VXOA_t$	Dependent Variable: ΔVXN_t	Dependent Variable: ΔVXD_t	Dependent Variable: $\Delta VDAX\_New_t$	Dependent Variable: $\Delta VCAC_t$	Dependent Variable: $\Delta VSTOXX_t$
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: 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 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: AR(1) Model							
	Dependent Variable: **ΔVIX_t**	Dependent Variable: **$\Delta VXOA_t$**	Dependent Variable: **ΔVXN_t**	Dependent Variable: **ΔVXD_t**	Dependent Variable: **$\Delta VDAX\_New_t$**	Dependent Variable: **$\Delta VCAC_t$**	Dependent Variable: **$\Delta VSTOXX_t$**
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**

Panel B: VAR Model							
	Dependent Variable: **ΔVIX_t**	Dependent Variable: **$\Delta VXOA_t$**	Dependent Variable: **ΔVXN_t**	Dependent Variable: **ΔVXD_t**	Dependent Variable: **$\Delta VDAX\_New_t$**	Dependent Variable: **$\Delta VCAC_t$**	Dependent Variable: **$\Delta VSTOXX_t$**
	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 3: Forecasting with the Univariate Autoregressive and VAR models. Panel A: The entries report results from the estimation of a univariate AR(1) for the daily changes *ΔIV* of each implied volatility index. The specification $\Delta IV_t = c_1 + \lambda_1 \, \Delta IV_{t-1} + \varepsilon_t$ is used. **Panel B:** The entries report the estimated coefficients of a VAR, for the set of the eight 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.

	Dependent Variable: **ΔVIX_t**	Dependent Variable: **$\Delta VXOA_t$**	Dependent Variable: **ΔVXN_t**	Dependent Variable: **ΔVXD_t**	Dependent Variable: **$\Delta VDAX\_New_t$**	Dependent Variable: **$\Delta VCAC_t$**	Dependent Variable: **$\Delta VSTOXX_t$**
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)*
$PC2_{t-2}$	**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 4: Forecasting with the Principal Components Analysis 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 $PC1$, $PC2$, $PC3$ and $PC4$ derived from the set of the eight 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							
	Dependent Variable: **ΔVIX_t**	Dependent Variable: **$\Delta VXOA_t$**	Dependent Variable: **ΔVXN_t**	Dependent Variable: **ΔVXD_t**	Dependent Variable: **$\Delta VDAX\_New_t$**	Dependent Variable: **$\Delta VCAC_t$**	Dependent Variable: **$\Delta VSTOXX_t$**
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							
	Dependent Variable: **ΔVIX_t**	Dependent Variable: **$\Delta VXOA_t$**	Dependent Variable: **ΔVXN_t**	Dependent Variable: **ΔVXD_t**	Dependent Variable: **$\Delta VDAX\_New_t$**	Dependent Variable: **$\Delta VCAC_t$**	Dependent Variable: **$\Delta VSTOXX_t$**
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 5: 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 $(1+\varphi L)\Delta IV_t = (1+\theta L)\varepsilon_t$ 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	1.01	1.03	1.01	0.94	1.04	1.01
MAE	0.68	0.64	**0.70***	**0.64****	0.67	0.71	0.70
MCP	50.16%	**54.22%****	**56.01%***	**53.41%****	52.03%	48.98%	52.03%
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 6: 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 economic variables model (Panel B), the AR(1) model (Panel C), the VAR model (Panel D), and the PCA model (Panel E), the 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.

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	7.14%	6.98%	4.22%	8.44%	1.88%	3.61%	2.18%
LRunc	**5.29****	**4.55****	0.83	**12.85***	**17.11***	2.85	**13.50***
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 7: 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 LR_{unc} of unconditional coverage for all implied volatility indices. 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), the AR(1) model (Panel B), the VAR model (Panel C), the PCA model (Panel D), the ARIMA(1,1,1) model (Panel E) and the 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	0.0113	0.0236	0.0285	0.0549	0.0392	-0.0226
95% CI	*(-0.07, 0.09)*	*(-0.06, 0.10)*	*(-0.06, 0.11)*	*(-0.04, 0.15)*	*(-0.08, 0.16)*	*(-0.17, 0.12)*
A_p	0.0731	0.1441	0.1590	0.5765	0.3440	-0.1541
95% CI	*(-0.66, 0.81)*	*(-0.40, 0.72)*	*(-0.33, 0.67)*	*(-0.51, 1.67)*	*(-0.71, 1.45)*	*(-1.24, 0.90)*
	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 8: 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 (*CI*). The strategy is based on point forecasts obtained from the economic variables model (Panel A), the AR(1) model (Panel B), the VAR model (Panel C), the PCA model (Panel D), the ARIMA(1,1,1) model (Panel E), and the ARFIMA(1,*d*,1) model (Panel F). For comparison purposes, 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	0.0458	**0.0803***	0.0725	0.0729	0.0587	-0.0341
95% CI	*(-0.03, 0.12)*	*(0.00, 0.16)*	*(-0.01, 0.15)*	*(-0.02, 0.16)*	*(-0.06, 0.18)*	*(-0.18, 0.11)*
A_p	0.4332	0.5480	0.4219	0.8336	0.5329	-0.2506
95% CI	*(-0.30, 1.19)*	*(-0.01, 1.11)*	*(-0.08, 0.93)*	*(-0.23, 1.94)*	*(-0.56, 1.61)*	*(-1.34, 0.82)*
	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 9: 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 (CI). The trading game is based on interval forecasts obtained from the economic variables model (Panel A), the AR(1) model (Panel B), the VAR model (Panel C), the PCA model (Panel D), the ARIMA(1,1,1) model (Panel E) and the ARFIMA(1,d,1) model (Panel F). For comparison purposes, 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.