Forecasting Volatility in Asian and European Stock Markets with Asymmetric GARCH Models

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INDEX

Abstract

This paper investigates the forecasting performance of three popular variants of asymmetric GARCH models, namely VS-GARCH, GJR-GARCH and Q-GARCH, with the symmetric GARCH(1,1) model as the benchmark. The application involves three Asian and ten European stock price indexes. Forecasts produced by each asymmetric GARCH model and each index are evaluated using a common set of classical criteria, as well as forecast combination techniques with constant and non-constant weights. With respect to the standard GARCH specification, the asymmetric models generally lead to better forecasts in terms of both smaller forecast errors and lower biases. In-sample forecast combination regressions are better than those from single Mincer-Zarnowitz regressions. The out-of-sample performance of combining forecasts is less satisfactory, irrespective of the type of weights adopted.

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1. INTRODUCTION

Asymmetric GARCH models (see Hentschel, 1995, for a survey) extend the seminal contributions by Engle (1982) and Bollerslev (1986) to incorporate the asymmetric impacts of shocks or news of equal magnitude but opposite sign on the conditional variance of asset returns. In this paper we investigate the forecasting performances of three popular variants of asymmetric GARCH specifications, namely Volatility Switching (VS-GARCH), GJR-GARCH and Quadratic (Q-GARCH), using the symmetric GARCH(1,1) as the benchmark. The application involves three Asian and ten European stock market indexes.

Following Poon and Granger (2003), it is possible to divide the current literature on forecasting volatility in financial markets in two main veins. The first one refers to models based on historical prices (time series approach), whereas the second comprises those techniques aimed at forecasting volatility from actual option prices via the link with the Black-Sholes's model (option implied standard deviation approach).

This paper belongs to the time series approach, which starts with the work by Taylor (1987) on forecasting the future volatility of the DM/$ exchange rate series. Dimson and Marsh (1990) investigate the forecasting performance of some simple models applied to the U.K. stock market, such as Random Walk (RW), Historical Average, Moving Average, Exponential Smoothing and linear regressions. Akgiray (1989) is the first who uses the GARCH model to forecast volatility, showing that the GARCH(1,1) outperforms some of the techniques discussed in Taylor (1987). On the contrary, Cao and Tsay (1992) point out that the Threshold Autoregressive model produces better forecasts than GARCH, Exponential GARCH e ARMA models on the U.S.A. stock market. The forecasting behaviour of the Stochastic Volatility (SV) model is even more controversial. On the one hand, Heynen (1995) and Yu (2002) confirm the validity of the SV model when applied to stock market indexes, on the other hand Dunis, Laws and Chauvin (2001) document some difficulties for this model to forecast exchange rate volatility.

Tse and Tung (1992) strongly prefer the Exponentially Weighted Moving Average model to the GARCH(1,1) for the Singapore stock market. This is mainly attributable to the non-stationary variances of Singapore stock market indexes, while the standard GARCH model imposes stationarity. Brailsford and Faff (1996) select the GJR-GARCH(1,1) as the best model for the Australian stock index, although they point out that the final choice is not independent of the adopted evaluation criteria. On the same Australian stock index, Walsh and Tsou (1998) reject the GARCH model, whereas Brooks (1998) is not able to select the most appropriate model for the Dow Jones composite. Finally, Franses and van Dijk (1996) compare RW, GARCH, Q-GARCH and GJR-GARCH specifications and show that Q-GARCH is the most successful in forecasting the volatility of stock price indexes for Italy, Spain, Germany and Sweden.

Such different and often contrasting results are mainly due to the lack of any common procedure to produce and evaluate competing sets of forecasts, especially in terms of number of time series subject to scrutiny, frequency of the data, forecasting horizons and loss functions.

With respect to the existing literature, this paper contains several distinguishing elements. First, a number of relevant Asian and European stock markets is analyzed. Second, samples and data frequencies are kept homogeneous throughout the empirical investigation. Third, forecasts produced by different models are compared using a common set of classical criteria and more recent forecast combination techniques with constant and non-constant weights.

The structure of the paper is as follows. Section 2 presents the main characteristics of the asymmetric GARCH models used in the empirical analysis. Section 3 is dedicated to a discussion of the criteria adopted to compare different sets of forecasts. In Section 4 the data set is briefly described, and the forecasting performance of each asymmetric GARCH model for each stock market index is analyzed. Section 5 contains some concluding comments.

2. ASYMMETRIC GARCH MODELS: VS-GARCH, GJR-GARCH AND Q-GARCH

Consider the following specification:

$$y_t = E\left(y_t \mid \Omega_{t-1}\right) + \varepsilon_t$$
$$\varepsilon_t = \sqrt{h_t}\eta_t,$$

where y_t indicates the returns on a single stock price index at time t, ε_t is the error term (shock) relative to returns y_t, η_t is independently and identically distributed with zero mean and unit variance, Ω_{t-1} is the past information available up to and including t-1, h_t is the conditional variance (or volatility) of the returns, defined as $h_t \equiv E\left(\varepsilon_t^2 \mid \Omega_{t-1}\right)$ for some non-negative function $h_t = h_t\left(F_{t-1}\right)$. The basic GARCH(1,1) model proposed by Bollerslev (1986) specifies the conditional volatility of returns h_t as a function of its one-period-lagged own values and squared shocks to returns, that is:

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}.$$

2.1
The GJR-GARCH model

This model has been introduced by Glosten, Jagannathan and Runkle (1993). It is based on a modification of the conditional variance equation of the basic GARCH(1,1) specification, which assumes that the parameter of ε_{t-1}^2 depends on the sign of the shock:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 (1 - \mathrm{I}[\varepsilon_{t-1} > 0]) + \gamma_1 \varepsilon_{t-1}^2 \mathrm{I}[\varepsilon_{t-1} > 0] + \beta_1 h_{t-1}\,, \tag{1}$$

where $\mathrm{I}[\cdot]$ is an indicator function. The non-negativity conditions for the conditional variance are $\alpha_0 > 0$, $(\alpha_1 + \gamma_1)/2 \geq 0$ and $\beta_1 > 0$, whereas the process is covariance-stationary if $(\alpha_1 + \gamma_1)/2 + \beta_1 < 1$. If this condition is satisfied, the unconditional variance is $\sigma^2 = \alpha_0 /(1 - (\alpha_1 + \gamma_1)/2 - \beta_1)$.

From equation (1) it is easy to notice that this model allows the coefficients of ε_{t-1}^2 to take different values corresponding to positive or negative shocks. Using equation (1), and assuming that the distribution of η_t is symmetric around zero, it is possible to obtain the 2-step ahead forecast for the conditional variance as:

$$\hat{h}_{t+2|t} = \mathrm{E}[\alpha_0 + \alpha_1 \varepsilon_{t+1}^2 (1 - \mathrm{I}[\varepsilon_{t+1} > 0]) + \gamma_1 \varepsilon_{t+1}^2 \mathrm{I}[\varepsilon_{t+1} > 0] + \beta_1 h_{t+1} \mid \Omega_t] \tag{2}$$

Equation (2) can be simplified by assuming that $\mathrm{E}[\mathrm{I}[\varepsilon_{t+1} > 0]] = P(\varepsilon_{t+1} > 0) = 0.5$ and $\mathrm{E}[\varepsilon_{t+1}^2 \mid \Omega_t] = h_{t+1}$, since ε_{t+1}^2 and the indicator function $\mathrm{I}[\varepsilon_{t+1} > 0]$ are uncorrelated:

$$\hat{h}_{t+2|t} = \alpha_0 + ((\alpha_1 + \gamma_1)/2 + \beta_1) h_{t+1}\,.$$

s-step ahead forecasts can be computed recursively as:

$$\hat{h}_{t+s|t} = \alpha_0 + ((\alpha_1 + \gamma_1)/2 + \beta_1) \hat{h}_{t+s-1|t}\,, \tag{3a}$$

or, without using previous forecasts:

$$\hat{h}_{t+s|t} = \alpha_0 \sum_{i=0}^{s-1} ((\alpha_1 + \gamma_1)/2 + \beta_1)^i + ((\alpha_1 + \gamma_1)/2 + \beta_1)^{s-1} h_{t+1}\,. \tag{3b}$$

2.2
The VS-GARCH model

This model has been proposed by Fornari and Mele (1996, 1997) as a generalization of the GJR-GARCH (1), where typically $\gamma_1 < \alpha_1$, that is shocks of the same magnitude but opposite sign have a different impact on the next-period volatility.

The VS-GARCH model originates from the intuition in Rabemananjara and Zakoïan (1993), according to which the asymmetric behaviour of h_t depends not only on the sign, but also on the dimension of the shock.

Fornari and Mele (1996) refer to an asymmetric behaviour of the volatility which is invertible as the dimension of the shocks varies. If shocks are small (large), positive (negative) shocks have higher impact on the volatility.

The equation for the conditional variance of a VS-GARCH(1,1) is:

$$h_t = (\alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1})(1 - \mathrm{I}[\varepsilon_{t-1} > 0]) + (\phi_0 + \phi_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1})\mathrm{I}[\varepsilon_{t-1} > 0]. \qquad (4)$$

The unconditional variance of this model is the same as in the GARCH(1,1), with the only difference that now the single coefficients are substituted with the arithmetic mean of the coefficients of the two regimes:

$$\sigma^2 = (\alpha_0 + \phi_0)/[1 - (\alpha_1 + \phi_1)/2 - (\beta_1 + \gamma_1)/2].$$

Fornari and Mele (1997) show that the kurtosis for this model is larger than that of a simple GARCH(1,1) with parameters equal to the mean between the parameters in the two regimes of the VS-GARCH.

Using expression (4), we can calculate 2-step-ahead forecasts as:

$$\begin{aligned}\hat{h}_{t+2|t} = \mathrm{E}[(\alpha_0 + \alpha_1 \varepsilon_{t+1}^2 + \beta_1 h_{t+1} \mid \Omega_t)(1 - \mathrm{I}[\varepsilon_{t+1} > 0]) + \\ (\phi_0 + \phi_1 \varepsilon_{t+1}^2 + \gamma_1 h_{t+1} \mid \Omega_t)\mathrm{I}[\varepsilon_{t+1} > 0].\end{aligned}$$

Recalling that ε_{t+1}^2 and the indicator function $\mathrm{I}[\varepsilon_{t+1} > 0]$ are uncorrelated, that $\mathrm{E}[\mathrm{I}[\varepsilon_{t+1} > 0]] = P(\varepsilon_{t+1} > 0) = 0.5$ and that $\mathrm{E}[\varepsilon_{t+1}^2 \mid \Omega_t] = h_{t+1}$, the following simplification applies:

$$\hat{h}_{t+s|t} = \alpha_0 + ((\alpha_1 + \phi_1)/2 + (\beta_1 + \gamma_1)/2)\hat{h}_{t+s-1|t}, \qquad (5a)$$

and the general recursive expression can be obtained:

$$\hat{h}_{t+s|t} = \sum_{i=0}^{s-1} \alpha_0 + ((\alpha_1 + \phi_1)/2 + (\beta_1 + \gamma_1)/2)^i + \alpha_0 + ((\alpha_1 + \phi_1)/2 + (\beta_1 + \gamma_1)/2) h_{t+1}, \quad (5b)$$

which allows us to calculate s-period-ahead forecasts based on the knowledge of h_{t+1} only.

2.3
The Q-GARCH model

The Q-GARCH model is originally due to Sentana (1995). The equation for the conditional variance is:

$$h_t = \alpha_0 + \gamma_1 \varepsilon_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}. \quad (6)$$

With respect to the simpler GARCH(1,1) model, only the term $\gamma_1 \varepsilon_{t-1}$ is added, which allows for the asymmetric impact of positive and negative shocks. Equation (6) can be alternatively rewritten as:

$$h_t = \alpha_0 + \left(\frac{\gamma_1}{\varepsilon_{t-1}} + \alpha_1 \right) \varepsilon_{t-1}^2 + \beta_1 h_{t-1}.$$

The optimal *s*-step-ahead variance forecast for a Q-GARCH is then:

$$\hat{h}_{t+s|t} = \alpha_0 + \left(\frac{\gamma_1}{\hat{\varepsilon}_{t+s-1|t}^2} + \alpha_1 \right) \hat{\varepsilon}_{t+s-1|t}^2 + \beta_1 \hat{h}_{t+s-1|t}. \quad (7)$$

If γ_1 is negative, the impact of negative shocks is larger than the impact of positive shocks. Moreover, the asymmetry of the impact varies as the dimension of the shock varies, in particular the asymmetric impact decreases as the dimension of the shock increases.

The autocorrelation function and the condition for weak stationarity are identical to the GARCH(1,1) model. Since the index of kurtosis for ε_t is a positive function of the module of γ_1, the Q-GARCH model is able to rationalize excess kurtosis in asset returns.

2.4
Forecast errors

In order to evaluate the performance of the *s*-step-ahead forecast of the conditional variance, it is possible to define the associated forecast error as:[1]

$$v_{t+s|t} \equiv h_{t+s} - \hat{h}_{t+s|t} . \qquad (8)$$

For the GARCH(1,1) benchmark model, the optimal *s*-step-ahead forecast of the conditional variance can be calculated recursively from:

$$\hat{h}_{t+s|t} = \alpha_0 + \alpha_1 \hat{\varepsilon}^2_{t+s-1|t} + \beta_1 \hat{h}_{t+s-1|t} , \qquad (9)$$

where, by definition, $\hat{\varepsilon}^2_{t+i|t} = \hat{h}^2_{t+i|t}$ for i>0, and, for i≤0, $\hat{\varepsilon}^2_{t+i|t} = \varepsilon^2_{t+i}$, $\hat{h}_{t+i|t} = h_{t+i}$. Recursive substitution in expression (9) yields:

$$\hat{h}_{t+s|t} = \alpha_0 \sum_{i=0}^{s-1} \left(\alpha_1 + \beta_1\right)^i + \left(\alpha_1 + \beta_1\right)^{s-1} h_{t+1} . \qquad (10)$$

It is important to emphasize that h_{t+1} can be directly computed from observations y_t, y_{t-1}, …., given the knowledge of parameters α_0, α_1 and β_1.

Using definition (8) and the expressions for the optimal *s*-step-ahead forecast of the conditional variance (9) or (10), the forecast error for the GARCH(1,1) model is:

$$v_{t+s|t} = \alpha_1 v_{t+s-1} + \left(\alpha_1 + \beta_1\right) v_{t+s-1|t} , \qquad (11)$$

since $\hat{\varepsilon}^2_{t+i|t} = \hat{h}_{t+i|t}$ for i>0 and we define $v_t \equiv \varepsilon^2_t - h_t$. If we substitute recursively in equation (11) we obtain:

$$v_{t+s|t} = \alpha_1 \sum_{i=1}^{s-1} \left(\alpha_1 + \beta_1\right)^{i-1} v_{t+s-i} .$$

[1] *See, for instance, Franses and van Dijk (2000), pp. 190-194.*

Expressions for the forecast errors associated with the optimal *s*-step-ahead forecast of the conditional variance of models GJR-GARCH, VS-GARCH and Q-GARCH can be obtained in a similar way by substituting expressions (3a)-(3b), (5a)-(5b) and (7) into (8), respectively. Notice also that variance forecasts for each of the asymmetric GARCH models illustrated in Sections 2.1-2.3 are additive over time.[2]

The forecast error expression for the Q-GARCH model requires a more detailed comment. Indeed, although the asymmetric term $\gamma_1 \varepsilon_{t-1}$ in equation (6) has no effect on the forecast computation algorithm, since the expected value of ε_{t+i}, $i > 0$, is zero by assumption, nonetheless the presence of $\gamma_1 \varepsilon_{t-1}$ affects the forecast error:

$$
\begin{aligned}
\upsilon_{t+s|t} &\equiv h_{t+s} - \hat{h}_{t+s|t} \\
&= \gamma_1 \varepsilon_{t+s-1} + \alpha_1 (\varepsilon^2_{t+s-1} - \hat{\varepsilon}^2_{t+s-1|t}) + \beta_1 (h_{t+s-1} - \hat{h}_{t+s-1|t}) \\
&= \gamma_1 \varepsilon_{t+s-1} + \alpha_1 v_{t+s-1} + (\alpha_1 + \beta_1) \upsilon_{t+s-1|t} \\
&= \alpha_1 \sum_{i=1}^{s-1} (\alpha_1 + \beta_1)^{i-1} v_{t+s-i} + \gamma_1 \sum_{i=1}^{s-1} (\alpha_1 + \beta_1)^{i-1} \varepsilon_{t+s-i}.
\end{aligned}
$$

In this case, forecasts are still unbiased, since, given that $\mathrm{E}[v_{t+s-i} \mid \Omega_t] = \mathrm{E}[\varepsilon_{t+s-i} \mid \Omega_t] = 0$ for any $i = 1, ..., s-1$, $\mathrm{E}[v_{t+s|t} \mid \Omega_t] = 0$. Nevertheless, the conditional variance of $\upsilon_{t+s|t}$ is larger than the corresponding conditional variance of the GARCH(1,1) model, which in turn means that uncertainty associated to the forecast of h_{t+s} is now larger.

[2] *This is a useful property, since it justifies the use of linear forecast combination techniques in order to assess the predictive performance of different non-linear models.*

3. FORECASTING EVALUATION METHODS FOR ASYMMETRIC GARCH MODELS

3.1 Classical evaluation criteria

Define the loss differential as:

$$d_j = v^k_{n+j|n+j-1,a} - v^k_{n+j|n+j-1,b}, \qquad j=1,2,\ldots,m,$$

where $v^k_{n+j|n+j-1,a}$ and $v^k_{n+j|n+j-1,b}$ are the forecast errors at time $n+j$ computed as suggested in Section 2.4 using models a and b respectively, and k is equal to 2 (or 1) if the mean squared errors (or the mean absolute errors) are confronted.

Following Diebold and Mariano (1995), we concentrate our investigation on three tests. The first one is the so-called sign test (S test), whose asymptotic version is given by:

$$S = \frac{2}{\sqrt{m}}\sum_{j=1}^{m}\left(I[d_j > 0] - \frac{1}{2}\right) \sim N(0,1). \tag{12}$$

The underlying intuition of this statistic is simple. Assuming that the loss differential is IID, the number of positive observations in a sample of size m has a binomial distribution with parameters m and $1/2$. It is important to notice that the null hypothesis of this test is "median of the loss differential equal to zero", which coincides with the null of zero loss differential mean only if the distribution of the loss differential is symmetric (this is not always the case for the series we are about to analyze). Unfortunately, the S test does not take into consideration the magnitude of the spreads between the forecast errors of the two competing models.

The second statistic is the Diebold-Mariano test (DM test), which compares the module of the size of the forecast errors by testing whether the mean of the loss differential is significantly different from zero. In fact, it is possible to show that, if d_j is a covariance stationary time series, the asymptotic distribution of its sample mean is:

$$\sqrt{m}(\bar{d} - \mu) \sim N(0, f)$$

where:

$$\overline{d} = \frac{1}{m}\sum_{j=1}^{m}\left[\mathrm{L}(v_{n+j|n+j-1,a}) - \mathrm{L}(v_{n+j|n+j-1,b}) \right],$$

is the sample mean of the loss differential based on any loss function $\mathrm{L}[\cdot]$, *f* indicates the variance of the sample mean, whereas μ is the population mean of the loss differential. Thus, in large samples, under the null hypothesis of zero population mean of the loss differential, $\overline{d}$ has a standard normal distribution:

$$DM = \frac{\overline{d}}{\sqrt{\hat{f}}} \sim N(0,1), \qquad (13)$$

with $\hat{f}$ being a consistent estimator of the asymptotic variance of $\overline{d}$. Diebold and Mariano suggest to estimate *f* using the non-weighted sum of the autocovariances for d_j:

$$\hat{f} = \frac{1}{m}\sum_{i=-(h-1)}^{h-1} \hat{\gamma}_i(d),$$

h being the forecasting horizon where the forecast errors are confronted.

Such an estimate of the asymptotic variance is motivated by the structure of the *h*-step-ahead forecast error, which is a linear combination of the shocks occurred up to $h-1$ and thus is serially correlated up to order $h-1$. Obviously, for $h=1$, $\hat{f}$ is $\hat{\gamma}_0(d)$, that is the variance of d_j.

Alternatively, the DM test is a t-test of zero population mean of the loss differential, which considers that the loss differential is not necessarily a white noise process. As far as the choice of the loss function is concerned, it is important to notice that for most of the series under scrutiny the forecast errors and the loss differential are characterized by aberrant observations (larger, in absolute value, than three standard deviations), as well as by ARCH effects. Consequently, specifying L[.] with the absolute value function seems to be more appropriate, given that the traditional quadratic loss function would imply very large standard deviations and force the statistics to be in the non-rejection region most of the times.

A simple Lagrange Multiplier test reveals the presence of first-order ARCH effects in the loss differentials with L[.] specified with the absolute value function[3]. This result justifies the

[3] *Results from the Lagrange Multiplier ARCH test are not reported here to economize space.*

introduction of the Newey-West test (NW test), which is again a t-type statistic of the null hypothesis of zero mean loss differential. The difference with the DM test is given by the variance-covariance matrix, which in this case is estimated according to Newey and West (1987) and thus it is robust to autocorrelation and ARCH effects.

In many empirical studies (see, among others, Akgiray, 1989; Brailsford and Faff, 1996) more traditional criteria are used to evaluate the forecasting performance of alternative non-linear GARCH models. Among the most commonly adopted measures are the mean squared (MSPE), the mean absolute (MAPE) prediction error, and, given the presence of aberrant observations and outliers in stock market returns, the median squared (MedSPE) and the median absolute (MedAPE) prediction error. For instance, when volatility is the object of the prediction exercise, MSPE is defined as:

$$\text{MSPE} = \frac{1}{m}\sum_{j=0}^{m-1}(\hat{h}_{n+s+j|n+j} - h_{n+s+j})^2 \ . \tag{14}$$

A popular approach to evaluate the unbiasedness of the forecast $\hat{h}_{n+s+j|n+j}$ is the regression originally proposed by Mincer and Zarnowitz (1969) and further discussed in Fair and Shiller (1989, 1990) [4]:

$$h_{n+s+j} = a + b\hat{h}_{n+s+j|n+j} + e_{n+s+j}, \qquad j = 0,....,m-1, \tag{15}$$

where $a = 0,\ b = 1$ indicate, together with $\mathrm{E}(\hat{e}_{n+s+j}) = 0$, unbiased forecasts.

The main obstacle to the practical use of these criteria is that the true volatility h_{n+s+j} in (14) and (15) is unobserved. A commonly used solution is to substitute h_t with the squared shocks $\varepsilon^2_{n+s+j} = \eta^2_{n+s+j}h_{n+s+j}$. Since $\mathrm{E}[\eta^2_{n+s+j}] = 1$, ε^2_{n+s+j} is an unbiased estimate of h_{n+s+j}. Out-of sample values of the squared shocks are replaced with the time series of realized volatility $h_{real,n+s+j}$, where:

$$h_{real,n+s+j} = \left(y_{n+s+j} - \bar{y}\right)^2$$

is the series of squared deviations of returns at time $n+s+j$ from their sample mean $\bar{y}$.[5]

[4] *See also Pagan and Schwert (1990), Day and Lewis (1992), Lamoureux and Lastrapes (1993). It is advisable to use the Newey-West method to calculate the regression standard errors, since the error terms are generally serially correlated and heteroskedastic.*

[5] *See Dacorogna et al. (2001), pp. 243-247, for a similar definition of realized volatility.*

It is worth noticing that most empirical studies find that volatility forecasts based on linear and asymmetric GARCH models are quite unsatisfactory, with very large MSPE and very low R^2 value from regression (15). Moreover, the forecast unbiasedness hypothesis of $a = 0$ in equation (15) is generally rejected (e.g. Andersen and Bollerslev, 1998, Christodoulakis and Satchell, 1998).

3.2
Forecast combination

The aim of the statistical criteria presented in Section 3.1 is to determine, among different competing models, the most accurate forecast relative to a pre-specified loss function. In many practical situations this is not an easy task, since each model is able to capture only a limited amount of information contained in the series of interest. If this is the case, an alternative and more appealing strategy is forecast combination or forecast encompassing (see Diebold and Lopez, 1996 for an exhaustive survey).

A forecast encompassing test allows us to verify whether a single forecast incorporates all the information included in the forecasts generated by alternative competing models. The intuition behind this approach is due to Nelson (1972) and Cooper and Nelson (1975), whereas its formalization appears in Chong and Hendry (1986).

Two forecasts are confronted, $\hat{y}^a_{t+h|t}$ and $\hat{y}^b_{t+h|t}$, which have been obtained by two different models *a* and *b*. The forecast encompassing test is based on the following regression:

$$y_{t+h} = \beta_a \hat{y}^a_{t+h|t} + \beta_b \hat{y}^b_{t+h|t} + \varepsilon_{t+h|t} . \tag{16}$$

If $(\beta_a, \beta_b) = (0,1)$ or $(\beta_a, \beta_b) = (1,0)$, then model *b* encompasses model *a* (and viceversa). If this is not true, both forecasts include useful information on y_{t+h}. Standard hypothesis tests can be used, provided the time series involved in regression (16) are covariance-stationary and, for $h > 1$, serial correlation of the error term $\varepsilon_{t+h|t}$ is taken into consideration.

A similar approach is proposed by Fair and Shiller (1989, 1990), which is based on the regression:

$$y_{t+h} - y_t = \beta_a (\hat{y}^a_{t+h|t} - y_t) + \beta_b (\hat{y}^b_{t+h|t} - y_t) + \varepsilon_{t+h|t} , \tag{17}$$

and accommodates the case of non-stationary, integrated forecasts using differences. The encompassing hypotheses can be tested in the present framework by invoking asymptotic normality of standard statistics. If the encompassing test rejects the null hypothesis, this evidence should be interpreted in favour of forecast combination. Even if the forecasts obtained by different models have white noise errors, this is not necessarily the case for the forecast combination. It is then important to allow for an error with an adequate ARMA(p,q) structure, when estimating the weights for the forecast combination. Moreover, additional information can be obtained if part of the forecasts is reserved to evaluate the empirical performance of the forecast combination.

4.
EMPIRICAL RESULTS

The empirical application involves three Asian as well as ten European stock price indexes, namely Hang Seng (Hong Kong, China), Straits Times New (Singapore), Tokyo SE Topix (Japan), London FSTE 100 (U.K.), CAC 40 (France), DAX 30 Performance (Germany), Milan Mib Historical (Italy), BBL 30 (Belgium), Swiss Market (Switzerland), Athens SE General (Greece), PSI General (Portugal), Madrid SE General (Spain) and Amsterdam AEX (EOE) (Holland). Table 1 reports sample sizes and frequencies for each series.

Table 2 presents some descriptive statistics on weekly and daily percentage returns (y_t) of each stock price index (p_t), defined as $y_t = 100[\ln(p_t) - \ln(p_{t-1})]$. From a simple inspection of this table, some key features which are typical of most financial time series are confirmed for these data. In particular, kurtosis is always larger than 3, especially for daily returns, whereas skewness is generally negative.

The non-linear GARCH models discussed in Section 2 are now estimated to rationalize the stylized facts of Table 2. Their empirical performance is then compared with the standard linear GARCH(1,1) specification taken as the benchmark model.

4.1
Results from classical evaluation criteria

We have adopted the following procedure to obtain alternative forecasts of conditional volatility. Each asymmetric GARCH model has been estimated on a rolling window, whose size is constant within each stock index but varies across different indexes according to Table 3. Each window of constant size rolls over the sample step by step. At each step, a new window is formed by deleting the first observation and adding one observation to the last observation of the previous window. For each window, each series and each model, h-step-ahead forecasts are obtained, h=1,…,5. For the first five indexes presented in Table 1, since they are observed on a common sample, we use a 7-year rolling window, from the first week of 1987 to the last week of 1993. Consequently, at the first step we obtain volatility forecasts for the first 5 weeks of 1994, at the second step we generate volatility forecasts from week 2 to week 7 of 1994, and so on until the last week of 2000. The result is given by five series of h-step-ahead forecasts, h=1,…,5, each series formed by 365 observations (number of weeks from the beginning of 1994 to the end of 2000). These series of forecasts are then summarized by computing the classical evaluation criteria described in Section 3.

Table 4 reports detailed results about the forecast accuracy analysis based on classical evaluation criteria. Each section of Table 4 refers to a specific stock index, whereas the whole set of evaluation criteria is applied to each asymmetric GARCH model - whose specification is always of order (1,1) for the conditional variance and equal to the simple constant term for the mean equation - and calculated for each of the five forecasting horizons. In order to facilitate the comparison between each asymmetric specification and the benchmark GARCH(1,1) model, the reported values of MSPE, MedSPE, MAPE, and MedAPE are equal to the calculated values divided by the corrisponding values obtained using the GARCH(1,1) model[6]. The last three columns of each section of Table 4 show the p-values for tests S, DM and NW. Once again, each asymmetric GARCH model is confronted with the standard GARCH(1,1) on the same forecasting horizon.

For the DM test we have preferred the absolute value loss function to the popular quadratic specification, since the latter amplifies the largest values of the loss differential (sometimes up to thirty times). In this way, the standard deviation of the loss differential could be up to twenty times larger than the one obtained using the absolute value loss function. The DM test, which is in essence a t-test of the null hypothesis of zero constant robust to residual autocorrelation, is affected by this phenomenon and gives rise to small calculated values and large p-values. In addition, we have used the S test, since it is based on the median, instead of the mean, of the loss differential. This is useful when, as in our context, the values of the loss differentials are characterized by extreme observations, which affect the mean, but not the median, of the distribution. Since the loss differentials are often asymmetric, the DM and S tests lead to conclusions about the null hypothesis which are often conflicting.

The loss differentials which are at the heart of the statistics reported in Table 4 show, for all models and forecast horizons, several extreme observations. Consequently, the NW test has been recalculated using the series of the loss differentials, once all the outliers have been removed. We define as an outlier in the series of the loss differential any observation that is larger than the triple of the loss differential standard deviation, that is when $\left|d_j\right| > r\sigma,$ with $r = 3$. The choice of $r = 3$ has demonstrated to be appropriate for all series of the loss differential. P-values of the recalculated NW test are reported in Table 5.

From Tables 4 and 5 some interesting comments emerge. First, forecasting with GJR-GARCH and Q-GARCH does not yield a significant reduction of the forecast error relative to the GARCH(1,1), since in general the calculated values for MSPE, MedSPE, MAPE and MedAPE are close to one. The only exception is Japan, when the GJR-GARCH model is used. Second, these results are confirmed if we take into consideration the modified version of the NW test reported in Table 5 (with the exceptions of Greece and Japan when again the GJR-GARCH model is used, and Portugal, Holland and China relative to the Q-GARCH specification). Third,

[6] Thus, for example, the first column of each section reports the percentage value of the MSPE criterion for each asymmetric model and forecasting horizon with respect to the MSPE of the GARCH(1,1) for the same forecasting horizon.

the VS-GARCH is the model whose forecasting performance is less close to the GARCH(1,1), since the values taken by the four measures of forecast error are generally very far from unity. Four, if we concentrate on the VS-GARCH, the measures of forecast error with values significantly less than unity are based, in all cases, on the median of the forecast error, since the forecasts produced by the VS-GARCH are more volatile than those of GJR-GARCH and Q-GARCH. Finally, the tests of forecast accuracy confirm that the VS-GARCH is the model which is more distant from the linear GARCH. In particular, the null hypothesis of equality of the forecasting accuracy between VS-GARCH and GARCH(1,1) is rejected in 62% of the cases. For at least seven of the analyzed stock indexes (Holland, Belgium, France, Italy, Switzerland, Spain and Japan) the VS-GARCH model outperforms the linear GARCH, as well as the remaining asymmetric models.

In Table 6 the main results from the Mincer-Zarnowitz regression (15) are reported. First, the R^2 values are low, typically less than 0.1. Second, the forecasts obtained with the simple GARCH model are often biased. Third, the forecasting performance of GJR-GARCH and Q-GARCH is better than GARCH. A possible explanation is that modelling asymmetries contributes to the reduction of the magnitude of the bias. Fourth, the more flexible VS-GARCH generates forecasts with small bias, with the exception of U.K., Italy, Greece and Japan, where biases measured both in terms of slope and intercept are significant. Finally, in some cases (namely China, Italy and Greece) none of the analyzed models is able to produce forecasts with a R^2 in the Mincer-Zarnowitz regression larger than 0.03.

Overall, the forecasting performance of each single model is unsatisfactory. For this reason it is interesting to investigate the potential complementarieties among alternative individual models using a forecast combination approach.

4.2
Results from forecast combination

The most popular technique of forecast combination is a regression involving the whole set of competing forecasts with associated time-invarying coefficients (weights) and a constant term, as described in Granger and Ramanathan (1984). The assumption of constant weights is obviously restrictive. As a matter of fact, the series we would like to forecast are the shocks $\varepsilon^2_{n+s+j} = \eta^2_{n+s+j} h_{n+s+j}$, which are unbiased estimators of h_{n+s+j}, and widely vary in time according to the evolution of volatility.

If constant weights are assumed in the linear combination, it is not possible to take into account the actual and highly volatile behaviour of the series of interest, as well as the temporal changes in the accuracy of the combined forecasts. Thus, we have also proposed a forecast combination technique with variable weights.

In order to implement the forecast combination with constant coefficients, we have divided the sample of forecasts obtained by each of the four competing models in two parts. The first subsample is dedicated to the estimation of the weights of the linear combination, whereas the second is used to verify whether the set of weights obtained in the first part can replicate the linear combination out of sample.[7] More specifically, we used 70% of the forecast sample to estimate the weights and the remaining 30% to evaluate the out-of-sample performance of the forecast combination. We omit to present the results of the encompassing forecast test into detail, since it always rejects the irrelevance of any of the selected models in the forecast combination.

Table 7 presents the estimated weights of the linear combination of forecasts for each stock index and forecasting horizon. It is informative to compare the R^2 values from the forecast combination regressions of Table 7 with those from the Mincer-Zarnowitz regressions presented in Table 6 for each single model. The forecast combination leads to a generalized increase of the R^2 values, thus suggesting that different models include complementary information which can be used to better approximate actual volatility.

Table 8 refers to the out-of-sample forecast performance of the forecast combination technique. Table 8 reports both the forecast evaluation criteria applied to each single model and the results from the Mincer-Zarnowitz regression. Unfortunately, the good in-sample performance of the forecast combination technique is not always replicated out of sample.

Despite the values taken by MSPE, MedSPE, MAPE and MedAPE are less than unity in several cases (i.e. the non-linear models outperform the simple GARCH (1,1)), and the tests for forecast accuracy reject the null hypothesis, the R^2 values of the Mincer-Zarnowitz regressions are generally less than the R^2 values relative to the in-sample combinations, and the R^2 values obtained from each single model. A reasonable explanation is that the large volatility characterizing the series of the squared shocks does not allow to generalize to the second subsample the weights which have been estimated on the first subsample.

A simple way to take into account time in the forecast combination regression is to include a linear trend and/or interactions of the existing regressors (forecasts) with a linear trend. Such a way of dealing with time could be reasonable if the weights are trend-varying, which is not our case. Figure 1 shows the temporal evolution of the five combination coefficients (constant included) relative to the 5-step-ahead forecasts for Italy. Specifically, C(1) is the coefficient of the GARCH forecast, C(2) is relative to GJR-GARCH, C(3) is the Q-GARCH coefficient and C(4) is the coefficient associated to VS-GARCH. All coefficients have been estimated using Recursive Least Squares. It is easy to see that each coefficient shows ample oscillations of both signs, which are hardly compatible with a linear trend.

In order to incorporate variable weights, a preferable approach is to estimate the parameters of the forecast combination within a rolling window of a fixed sample size, and then use those estimates to combine the forecasts of each single model starting from the last observation included in the rolling window. The sample size of the combined forecasts is equal to the difference between the sample size of the individual forecasts and the number of observations defining the rolling window. The number of observations of the rolling window is not the same for each stock index: among several alternatives (namely 15, 20, 25, 30, 35 and 40 observations), the one with the highest R^2 in the Mincer-Zarnowitz regression has been selected.

Table 9 reports the sample size of each rolling window, whereas Table 10 shows the results of the forecast combination technique with variable coefficients. The values taken by the forecast

[7] *Forecast sample sizes are different for each selected index and coincide with the rolling windows indicated in Table 4.*

error measures and the accuracy evaluation tests suggest that out-of-sample forecast combination outperforms only partially the regression method. Actually, the R^2 value of the Mincer-Zarnowitz regression is not always larger than the corresponding R^2 value of the regression approach, while better results are obtained in terms of reduction of the forecast bias. When evaluated out of sample, the empirical performance of the regression method with constant or variable coefficients is not superior to the forecast results produced by individual linear and non-linear GARCH models.

5. CONCLUSIONS

The comparison between the forecasting accuracy of GARCH, GJR-GARCH, QGARCH and VS-GARCH does indicate neither a dominant model, nor a dominant country. With respect to the standard GARCH specification which ignores potential asymmetries in asset returns, the asymmetric models generally lead to better forecasts in terms of both smaller forecast errors and lower biases. The model which is empirically less close to the simple linear GARCH is the VS-GARCH.

However, the volatility forecasts which have been generated using the four asymmetric models are unsatisfactory, especially when evaluated on the basis of the R^2 values associated to the Mincer-Zarnowitz regression, which is low in most of the cases.

Individual models take into account only a part of the actual behaviour of the series, tending to play a complementary role in explaining observed volatility. This is confirmed by the forecast combination regression applied to the sample where the combination weights are estimated, which produces significantly higher R^2 values than those obtained from the individual Mincer-Zarnowitz regressions. When evaluated out of sample, the performance of the regression method is less satisfactory. Finally, the alternative technique of combining different forecasts with variable weights does not seem to represent a fully convincing solution.

A more promising direction of research would be the assessment of the forecasting performance of multivariate asymmetric GARCH models. Since most of the multivariate extensions of single equation GARCH models have been proposed by the econometric literature only recently (see, for instance, McAleer, 2004, for a critical survey), extensive studies on their predictive abilities are still to be undertaken. Those investigations are on our future research agenda.

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Table 1. Sample size and frequency for ten European and three Asian stock price indexes

Stock markets	Frequency (# Observ.)	Sample
Holland - Amsterdam AEX (EOE)	Daily (3788), weekly (757)	(07/01/1987 - 13/07/2001)
Belgium - BBL 30	Daily (3788), weekly (757)	(07/01/1987 - 13/07/2001)
Germany - Dax 30 Performance	Daily (3788), weekly (757)	(07/01/1987 - 13/07/2001)
U.K. - London FTSE 100	Daily (3788), weekly (757)	(07/01/1987 - 13/07/2001)
Italy - Milan Mib Historical	Daily (3788), weekly (757)	(07/01/1987 - 13/07/2001)
France - CAC 40	Daily (3653), weekly (730)	(09/07/1987 - 13/07/2001)
Spain - Madrid SE General	Daily (3528), weekly (705)	(01/05/1988 - 13/07/2001)
Portugal - PSI General	Daily (3528), weekly (705)	(01/05/1988 - 13/07/2001)
Switzerland - Swiss Market	Daily (3398), weekly (679)	(01/07/1988 - 13/07/2001)
Greece - Athens SE General	Daily (3333), weekly (666)	(30/09/1988 - 13/07/2001)
China - Hang Seng	Daily (3320), weekly (664)	(24/10/1988 - 13/07/2001)
Singapore - Straits Times (New)	Daily (3320), weekly (664)	(24/10/1988 - 13/07/2001)
Japan - Tokyo SE Topix	Daily (3320), weekly (664)	(24/10/1988 - 13/07/2001)

Notes to Table 1: The second column refers to the frequency of the data as well as the number of observations used in the empirical analysis; dates are reported in the format dd/mm/yyyy.

Table 2. Descriptive statistics on daily and weekly returns

Stock markets	Mean	Med	Min	Max	Var	Skew	Kurt
Daily returns							
Holland	0.042	0.040	-12.779	11.182	1.439	-0.589	14.872
Belgium	0.029	0.000	-12.531	8.943	0.900	-0.514	22.749
Italy	0.021	0.000	-8.476	6.216	1.487	-0.493	6.565
U.K.	0.031	0.019	-13.029	7.597	1.001	-1.058	17.847
Germany	0.038	0.037	-13.710	7.288	1.723	-0.760	11.453
France	0.033	0.000	-10.138	8.225	1.579	-0.415	8.187
Portugal	0.020	0.000	-10.814	7.572	0.850	-0.639	18.656
Spain	0.035	0.000	-8.611	6.362	1.228	-0.415	8.303
Switzerland	0.045	0.039	-11.112	7.462	1.133	-0.734	12.073
Greece	0.063	0.000	-10.646	13.749	3.375	0.131	8.066
China	0.048	0.000	-24.520	17.247	3.040	-0.920	23.659
Singapore	0.020	0.000	-10.207	14.868	1.755	0.146	15.093
Japan	-0.016	0.000	-7.365	9.116	1.454	0.222	7.880
Weekly returns							
Holland	0.208	0.418	-17.362	11.278	5.953	-0.991	8.584
Belgium	0.146	0.205	-16.719	10.268	4.941	-0.648	8.804
Italy	0.108	0.168	-11.487	12.425	8.474	-0.074	4.076
U.K.	0.152	0.273	-24.862	7.947	5.257	-1.760	21.482
Germany	0.196	0.269	-14.079	11.945	7.667	-0.497	4.934
France	0.169	0.162	-11.972	9.904	7.512	-0.133	3.899
Portugal	0.085	0.017	-14.876	13.692	5.875	-0.129	8.570
Spain	0.174	0.222	-11.506	11.744	6.105	-0.150	4.729
Switzerland	0.222	0.309	-14.640	11.280	5.402	-0.461	6.158
Greece	0.307	-0.098	-19.543	22.220	19.956	0.480	6.286
China	0.237	0.482	-20.977	13.228	13.429	-0.756	5.466
Singapore	0.102	-0.019	-13.640	14.615	10.094	-0.122	5.638
Japan	-0.083	-0.069	-10.849	13.406	7.508	0.074	5.122

Notes to Table 2: All descriptive statistics are calculated using the sample sizes reported in Table 1; Mean $= \frac{1}{n}\sum_{t=1}^{n} y_t \equiv \hat{m}$; Med = median; Min = minimum value; Max = maximum value; Var = $\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{m})^2 \equiv \hat{s}^2$, Skew $= \frac{1}{n}\sum_{t=1}^{n}\frac{(y_t - \hat{m})^3}{\hat{s}^3}$, Kurt = $\frac{1}{n}\sum_{t=1}^{n}\frac{(y_t - \hat{m})^4}{\hat{s}^4}$.

Table 3. Size of the rolling window for each stock price index

Stock market	Size of the rolling window
Holland	365 weekly obs. (7 years)
Belgium	365 weekly obs. (7 years)
Germany	365 weekly obs. (7 years)
U.K.	365 weekly obs. (7 years)
Italy	365 weekly obs. (7 years)
France	363 weekly obs.
Spain	351 weekly obs.
Portugal	351 weekly obs.
Switzerland	338 weekly obs.
Greece	331 weekly obs.
China	330 weekly obs.
Singapore	330 weekly obs.
Japan	330 weekly obs.

Notes to Table 3: For the last eight indexes there is no correspondence with the number of years, since the size of the rolling window doesn't exactly fit with an integer number of years.

Table 4. Classical evaluation criteria for each stock price index

		Holland							**Belgium**						
Model	*h*	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***NW***	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***NW***
GJR	1	0.993	0.931	0.994	0.965	0.426	0.565	0.459	0.963	0.889	0.982	0.943	0.113	0.374	0.309
	2	0.990	0.930	0.994	0.964	0.408	0.432	0.471	0.948	0.937	0.970	0.968	0.033	0.006	0.094
	3	1.004	0.935	0.999	0.967	0.696	0.320	0.689	0.977	0.932	0.976	0.965	0.132	0.024	0.135
	4	1.004	0.913	0.999	0.955	0.794	0.374	0.793	0.979	0.932	0.976	0.965	0.134	0.002	0.108
	5	1.003	0.913	1.000	0.956	0.663	0.084	0.670	0.976	0.992	0.978	0.996	0.141	0.019	0.109
Q	1	0.994	0.961	0.996	0.980	0.622	0.714	0.638	0.991	0.996	0.992	0.998	0.273	0.374	0.384
	2	0.992	0.979	0.999	0.989	0.787	0.432	0.802	0.986	0.990	0.985	0.995	0.035	0.032	0.073
	3	1.000	0.947	1.004	0.973	0.111	0.004	0.090	0.991	0.950	0.989	0.975	0.060	0.032	0.073
	4	1.003	0.995	1.005	0.997	0.026	0.002	0.029	0.992	0.964	0.988	0.982	0.063	0.006	0.050
	5	1.003	0.969	1.008	0.985	0.041	0.000	0.026	0.991	1.003	0.988	1.002	0.076	0.041	0.047
VS	1	1.023	0.687	0.936	0.829	0.131	0.794	0.037	1.014	0.625	0.935	0.791	0.032	0.272	0.087
	2	1.061	0.521	0.904	0.722	0.000	0.496	0.004	1.004	0.501	0.886	0.708	0.005	0.000	0.015
	3	1.069	0.434	0.882	0.658	0.002	0.014	0.003	1.036	0.499	0.881	0.707	0.013	0.000	0.012
	4	1.065	0.384	0.869	0.619	0.004	0.001	0.003	1.056	0.397	0.875	0.630	0.021	0.000	0.012
	5	1.088	0.317	0.874	0.563	0.012	0.002	0.007	1.068	0.374	0.862	0.612	0.021	0.000	0.010
		Germany							**U.K.**						
GJR	1	0.990	0.898	0.988	0.948	0.484	0.105	0.394	1.056	0.927	1.019	0.963	0.145	0.794	0.208
	2	0.969	0.911	0.983	0.955	0.125	0.320	0.205	1.010	0.956	1.006	0.978	0.514	0.875	0.576
	3	1.004	1.001	0.992	1.001	0.549	0.374	0.595	0.994	0.928	1.002	0.963	0.499	0.875	0.506
	4	0.996	0.898	0.986	0.948	0.412	0.875	0.378	0.974	0.893	0.994	0.945	0.721	0.432	0.738
	5	1.000	0.977	0.986	0.988	0.337	0.496	0.340	0.982	0.936	1.002	0.967	0.671	0.794	0.635
Q	1	1.001	0.937	0.985	0.968	0.286	0.158	0.268	0.988	0.990	0.999	0.995	0.866	0.067	0.880
	2	0.990	0.885	0.978	0.941	0.077	0.067	0.131	0.975	0.982	0.989	0.991	0.480	0.053	0.520
	3	1.004	0.972	0.984	0.986	0.282	0.794	0.313	0.974	1.020	0.991	1.010	0.607	0.032	0.609
	4	1.006	0.908	0.981	0.953	0.341	0.958	0.280	0.974	0.930	0.986	0.964	0.309	0.875	0.311
	5	1.009	0.997	0.979	0.999	0.232	0.875	0.249	0.975	0.984	0.993	0.992	0.601	0.320	0.545
VS	1	1.059	0.789	0.974	0.888	0.497	0.191	0.470	1.111	1.292	1.113	1.137	0.000	0.000	0.000
	2	1.045	0.639	0.948	0.799	0.119	0.496	0.129	1.116	1.135	1.077	1.065	0.003	0.084	0.003
	3	1.067	0.617	0.956	0.786	0.222	0.958	0.216	1.149	1.025	1.066	1.012	0.017	0.014	0.025
	4	1.087	0.531	0.933	0.729	0.097	0.129	0.073	1.109	0.811	1.041	0.900	0.122	0.320	0.142
	5	1.108	0.530	0.944	0.728	0.156	0.041	0.143	1.141	0.633	1.022	0.796	0.417	0.958	0.380
		Italy							**France**						
GJR	1	6.075	0.778	1.231	0.882	0.462	0.053	0.538	0.985	1.007	0.981	1.004	0.222	0.104	0.049
	2	1.966	0.635	1.022	0.797	0.477	0.565	0.460	0.986	1.052	0.985	1.026	0.017	0.031	0.083
	3	1.230	0.563	0.951	0.750	0.277	0.565	0.261	0.996	1.071	0.996	1.035	0.197	0.319	0.160
	4	1.082	0.473	0.902	0.688	0.389	0.714	0.381	0.999	1.080	0.997	1.039	0.387	0.495	0.146
	5	1.068	0.415	0.881	0.644	0.232	0.320	0.181	1.009	1.022	1.004	1.011	0.574	0.713	0.219
Q	1	1.004	0.922	0.992	0.960	0.028	0.272	0.044	0.992	0.991	0.986	0.995	0.456	0.014	0.281
	2	1.004	0.940	0.992	0.970	0.027	0.272	0.020	0.995	1.091	0.994	1.044	0.109	0.052	0.605
	3	1.003	0.971	0.989	0.985	0.012	0.084	0.009	1.004	1.115	1.005	1.056	0.476	0.104	0.852
	4	1.003	0.994	0.992	0.997	0.048	0.432	0.035	1.011	1.133	1.007	1.065	0.799	0.372	0.882
	5	1.003	0.942	0.991	0.971	0.035	0.053	0.022	1.018	1.053	1.013	1.026	0.968	0.319	0.842
VS	1	1.013	0.867	0.995	0.931	0.236	0.432	0.255	1.047	0.637	0.923	0.798	0.002	0.052	0.002
	2	1.013	0.939	0.995	0.969	0.788	0.000	0.789	1.052	0.557	0.925	0.747	0.001	0.000	0.004
	3	1.008	0.979	0.990	0.990	0.272	0.000	0.272	1.087	0.568	0.935	0.754	0.003	0.001	0.002
	4	1.009	0.995	0.994	0.997	0.004	0.000	0.002	1.092	0.540	0.922	0.735	0.001	0.000	0.001
	5	1.008	0.871	0.991	0.934	0.000	0.000	0.000	1.113	0.484	0.924	0.696	0.007	0.000	0.002

Table 4. Classical evaluation criteria for each stock price index (continued)

Model	*h*	**Spain**							**Portugal**						
		MSPE	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***NW***	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***NW***
GJR	1	0.985	1.012	0.992	1.006	0.419	0.062	0.398	1.070	1.132	1.006	1.064	0.588	0.873	0.587
	2	0.969	0.952	0.986	0.976	0.066	0.048	0.088	1.044	1.011	0.999	1.006	0.814	0.122	0.758
	3	0.982	0.975	0.990	0.987	0.289	0.262	0.336	1.057	0.991	0.999	0.995	0.937	0.022	0.929
	4	0.973	0.967	0.986	0.983	0.228	0.122	0.196	1.043	0.985	0.998	0.992	0.862	0.022	0.848
	5	0.965	1.000	0.982	1.000	0.143	0.262	0.130	1.043	0.953	0.992	0.976	0.308	0.000	0.414
Q	1	0.988	0.976	0.990	0.988	0.196	0.150	0.267	1.024	1.129	1.001	1.062	0.991	0.105	0.973
	2	0.978	0.948	0.987	0.974	0.120	0.098	0.151	1.021	0.997	0.994	0.998	0.240	0.019	0.173
	3	0.984	0.959	0.989	0.979	0.245	0.150	0.270	1.022	0.985	0.991	0.993	0.179	0.001	0.140
	4	0.979	0.984	0.988	0.992	0.265	0.311	0.230	1.019	0.989	0.995	0.995	0.120	0.000	0.093
	5	0.977	1.053	0.987	1.026	0.294	0.182	0.243	1.016	0.900	0.988	0.949	0.007	0.000	0.007
VS	1	1.030	0.604	0.928	0.777	0.017	0.037	0.019	0.927	1.452	0.962	1.205	0.422	0.150	0.588
	2	1.015	0.415	0.880	0.644	0.000	0.000	0.001	0.874	1.067	0.907	1.033	0.181	0.150	0.277
	3	1.047	0.420	0.883	0.648	0.002	0.000	0.002	0.929	0.804	0.892	0.897	0.209	0.790	0.214
	4	1.051	0.355	0.872	0.596	0.006	0.000	0.002	0.933	0.625	0.855	0.791	0.167	0.423	0.124
	5	1.087	0.333	0.878	0.577	0.008	0.001	0.006	0.934	0.646	0.849	0.803	0.187	0.150	0.123
		Switzerland							**Greece**						
GJR	1	0.978	1.062	0.995	1.030	0.850	0.663	0.844	1.143	1.120	1.045	1.058	0.068	0.169	0.120
	2	0.967	0.998	0.987	0.999	0.316	0.744	0.386	1.100	1.129	1.047	1.063	0.014	0.003	0.019
	3	0.983	1.117	0.995	1.057	0.879	0.231	0.878	1.054	1.224	1.033	1.106	0.004	0.005	0.005
	4	0.975	1.089	0.983	1.044	0.392	0.586	0.409	1.019	1.129	1.031	1.063	0.006	0.005	0.006
	5	0.974	1.016	0.979	1.008	0.343	0.663	0.296	1.017	1.074	1.024	1.036	0.022	0.007	0.014
Q	1	1.002	1.069	1.007	1.034	0.346	0.663	0.502	1.026	1.068	1.017	1.033	0.159	0.700	0.270
	2	0.998	1.046	1.005	1.023	0.580	0.744	0.633	1.002	0.976	1.008	0.988	0.441	0.350	0.491
	3	0.996	1.118	1.006	1.057	0.490	0.192	0.508	1.000	0.984	0.997	0.992	0.910	0.111	0.918
	4	0.988	1.148	1.005	1.071	0.628	0.328	0.604	0.996	0.976	0.980	0.988	0.188	0.000	0.169
	5	0.991	1.113	1.006	1.055	0.611	0.514	0.552	0.955	0.953	0.959	0.976	0.054	0.000	0.027
VS	1	0.963	1.121	0.938	1.059	0.096	0.446	0.123	1.078	1.725	1.203	1.313	0.000	0.000	0.009
	2	0.945	0.960	0.912	0.980	0.015	0.586	0.035	1.082	1.644	1.173	1.282	0.010	0.000	0.014
	3	0.967	0.898	0.897	0.948	0.014	0.082	0.009	1.074	1.395	1.124	1.181	0.036	0.111	0.035
	4	0.972	0.770	0.883	0.878	0.003	0.001	0.004	1.088	1.125	1.098	1.061	0.087	0.956	0.065
	5	0.979	0.620	0.876	0.787	0.002	0.000	0.001	1.002	0.918	1.031	0.958	0.534	0.869	0.480
		China							**Singapore**						
GJR	1	1.204	0.912	0.999	0.955	0.276	0.582	0.988	1.115	0.974	1.045	0.987	0.203	0.186	0.428
	2	1.138	0.896	0.975	0.946	0.556	0.660	0.718	1.023	0.917	0.997	0.957	0.688	0.000	0.905
	3	1.057	0.901	0.961	0.949	0.823	0.582	0.609	0.999	0.927	0.976	0.963	0.724	0.000	0.254
	4	0.985	0.875	0.959	0.935	0.968	0.826	0.629	0.991	0.944	0.978	0.972	0.234	0.000	0.125
	5	1.072	0.781	0.962	0.884	0.844	0.186	0.731	0.987	0.932	0.972	0.965	0.109	0.000	0.030
Q	1	0.944	1.022	0.977	1.011	0.006	0.152	0.121	1.621	1.362	1.337	1.167	0.150	0.036	0.081
	2	0.861	1.041	0.933	1.020	0.024	0.015	0.023	1.116	1.406	3.782	1.186	0.286	0.000	0.252
	3	0.832	0.952	0.915	0.976	0.097	0.000	0.020	1.980	1.183	2.231	1.088	0.309	0.000	0.293
	4	0.747	0.863	0.893	0.929	0.133	0.000	0.043	1.432	1.325	1.234	1.151	0.312	0.000	0.305
	5	0.640	0.822	0.853	0.906	0.167	0.000	0.050	1.230	1.247	2.976	1.117	0.311	0.000	0.311
VS	1	1.578	2.135	1.166	1.461	0.183	0.000	0.087	1.012	1.744	1.077	1.321	0.933	0.000	0.857
	2	1.241	1.170	0.979	1.082	0.512	0.099	0.827	0.987	1.602	1.043	1.266	0.154	0.000	0.172
	3	0.935	0.709	0.823	0.842	0.848	0.322	0.139	0.985	1.506	1.036	1.227	0.285	0.000	0.143
	4	0.674	0.553	0.691	0.744	0.261	0.001	0.036	0.975	1.502	1.017	1.226	0.106	0.000	0.088
	5	0.478	0.383	0.612	0.619	0.205	0.000	0.029	0.972	1.424	1.009	1.193	0.116	0.000	0.086

Table 4. Classical evaluation criteria for each stock price index (continued)

Japan

Model	*h*	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***NW***
GJR	2	0.855	0.586	0.845	0.766	0.208	0.004	0.035
	3	0.854	0.537	0.846	0.733	0.251	0.006	0.011
	4	0.825	0.619	0.833	0.787	0.241	0.001	0.005
	5	0.817	0.563	0.809	0.750	0.295	0.000	0.004
Q	1	1.170	1.354	1.086	1.163	0.123	0.152	0.053
	2	1.226	1.332	0.963	1.154	0.308	0.152	0.249
	3	1.023	1.580	0.976	1.257	0.286	0.582	0.215
	4	1.234	1.235	0.912	1.111	0.312	0.441	0.312
	5	0.999	1.042	1.036	1.021	0.311	0.021	0.314
VS	1	0.776	0.871	0.885	0.933	0.089	0.741	0.697
	2	0.787	0.638	0.805	0.799	0.073	0.099	0.015
	3	0.846	0.479	0.801	0.692	0.240	0.048	0.001
	4	0.859	0.372	0.759	0.610	0.369	0.000	0.000
	5	0.840	0.281	0.712	0.530	0.410	0.000	0.000

Notes to Table 4: For each stock index and each asymmetric GARCH model, the entries of the first four columns are the calculated values from each evaluation criterion divided by the value taken by the same criterion when applied to the standard GARCH(1,1) model on the same forecasting horizon.

Table 5. NW test after removing extreme observations

		P-values of the NW test												
Model	*h*	***Holland***	***Belgium***	***Germany***	***U.K.***	***Italy***	***France***	***Spain***	***Portugal***	***Switzerl.***	***Greece***	***China***	***Sing.***	***Japan***
GJR	1	0.861	0.768	0.161	0.543	0.875	0.058	0.077	0.248	0.656	0.059	0.565	0.182	0.469
	2	0.877	0.522	0.067	0.734	0.654	0.176	0.081	0.769	0.579	0.005	0.304	0.058	0.020
	3	0.696	0.127	0.433	0.722	0.622	0.059	0.102	0.472	0.812	0.006	0.919	0.128	0.002
	4	0.540	0.220	0.229	0.248	0.906	0.047	0.071	0.577	0.805	0.009	0.385	0.197	0.000
	5	0.951	0.496	0.239	0.142	0.416	0.126	0.246	0.280	0.776	0.056	0.292	0.114	0.000
Q	1	0.986	0.667	0.103	0.889	0.187	0.263	0.084	0.728	0.686	0.979	0.417	0.064	0.067
	2	0.287	0.456	0.479	0.920	0.125	0.948	0.714	0.073	0.448	0.349	0.013	0.252	0.249
	3	0.150	0.317	0.428	0.635	0.012	0.459	0.399	0.030	0.503	0.422	0.002	0.304	0.307
	4	0.016	0.220	0.511	0.325	0.132	0.534	0.423	0.008	0.599	0.039	0.008	0.312	0.314
	5	0.019	0.143	0.246	0.358	0.110	0.666	0.661	0.000	0.411	0.174	0.006	0.270	0.521
VS	1	0.095	0.120	0.281	0.000	0.991	0.014	0.021	0.530	0.307	0.000	0.105	0.622	0.833
	2	0.004	0.000	0.037	0.063	0.000	0.010	0.000	0.980	0.027	0.000	0.752	0.717	0.002
	3	0.007	0.005	0.045	0.107	0.000	0.001	0.000	0.648	0.006	0.018	0.072	0.781	0.000
	4	0.006	0.005	0.006	0.259	0.000	0.003	0.000	0.168	0.006	0.121	0.001	0.476	0.000
	5	0.007	0.007	0.012	0.766	0.000	0.000	0.001	0.261	0.005	0.547	0.000	0.408	0.000

Notes to Table 5: The NW test is a standard t-test of the null hypothesis of zero constant, where the estimated variance-covariance matrix of the coefficients is computed using the Newey-West correction. Observations which exceed, in absolute value, three times the standard error of the loss differential have been removed.

Table 6. Mincer-Zarnowitz regression

		Holland					Belgium				
Model	h	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
GARCH	a	1.985	1.038	2.275	2.662	2.635	1.588	0.872	2.293	2.433	2.464
		(0.939)	(0.953)	(0.962)	(0.964)	(0.915)	(0.761)	(0.773)	(0.825)	(0.852)	(0.876)
	b	0.671	0.615	0.551	0.552	0.813	0.126	0.131	0.144	0.152	0.159
		(0.103)	(0.104)	(0.105)	(0.104)	(0.100)	(0.734)	(0.895)	(0.584)	(0.557)	(0.553)
	R^2	0.104	0.153	0.088	0.071	0.072	0.086	0.113	0.043	0.036	0.032
GJR	a	1.977	1.054	2.408	2.772	2.740	1.136	0.052	1.909	2.020	1.899
		(0.925)	(0.900)	(0.940)	(0.949)	(0.949)	(0.746)	(0.756)	(0.834)	(0.872)	(0.907)
	b	0.675	0.814	0.597	0.537	0.539	0.859	1.117	0.699	0.682	0.717
		(0.101)	(0.098)	(0.102)	(0.102)	(0.102)	(0.127)	(0.134)	(0.153)	(0.166)	(0.177)
	R^2	0.109	0.160	0.087	0.071	0.072	0.112	0.161	0.054	0.044	0.043
Q	a	1.971	1.041	2.310	2.698	2.669	1.517	0.660	2.169	2.293	2.308
		(0.926)	(0.901)	(0.940)	(0.950)	(0.952)	(0.756)	(0.768)	(0.827)	(0.857)	(0.884)
	b	0.669	0.804	0.602	0.538	0.538	0.766	0.961	0.628	0.603	0.607
		(0.100)	(0.097)	(0.100)	(0.101)	(0.100)	(0.127)	(0.133)	(0.148)	(0.158)	(0.167)
	R^2	0.109	0.159	0.090	0.073	0.073	0.091	0.125	0.047	0.039	0.035
VS	a	1.744	-1.549	2.020	2.741	4.014	1.254	-2.022	0.934	0.869	-0.379
		(1.027)	(1.059)	(1.248)	(1.332)	(1.372)	(0.790)	(0.789)	(0.983)	(1.132)	(1.309)
	b	1.101	2.194	1.343	1.230	0.852	1.146	2.521	1.655	1.878	2.687
		(0.188)	(0.238)	(0.330)	(0.399)	(0.450)	(0.190)	(0.234)	(0.349)	(0.467)	(0.610)
	R^2	0.086	0.189	0.043	0.025	0.010	0.091	0.242	0.058	0.043	0.051

Table 6. Mincer-Zarnowitz regression (continued)

		Germany					U.K.				
Model	h	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
GARCH	a	2.458	1.218	3.263	2.716	2.443	2.547	1.643	2.097	1.377	1.699
		(1.416)	(1.422)	(1.487)	(1.509)	(1.536)	(0.839)	(0.878)	(0.900)	(0.896)	(0.898)
	b	0.740	0.904	0.636	0.709	0.747	0.415	0.595	0.493	0.632	0.563
		(0.150)	(0.153)	(0.162)	(0.166)	(0.172)	(0.159)	(0.166)	(0.168)	(0.166)	(0.165)
	R^2	0.063	0.088	0.041	0.047	0.049	0.018	0.034	0.023	0.038	0.031
GJR	a	2.195	-0.151	3.470	2.271	1.904	3.107	2.080	2.141	1.247	1.616
		(1.408)	(1.430)	(1.566)	(1.628)	(1.705)	(0.667)	(0.723)	(0.769)	(0.785)	(0.807)
	b	0.805	1.141	0.648	0.826	0.888	0.284	0.488	0.469	0.642	0.565
		(0.155)	(0.163)	(0.185)	(0.199)	(0.215)	(0.114)	(0.126)	(0.135)	(0.138)	(0.142)
	R^2	0.069	0.118	0.033	0.045	0.045	0.017	0.040	0.032	0.056	0.042
Q	a	2.202	-0.215	3.206	2.261	1.785	2.510	1.280	1.745	0.912	1.335
		(1.484)	(1.531)	(1.680)	(1.769)	(1.868)	(0.832)	(0.905)	(0.953)	(0.967)	(0.987)
	b	0.825	1.180	0.702	0.846	0.924	0.421	0.674	0.576	0.751	0.656
		(0.171)	(0.184)	(0.209)	(0.227)	(0.246)	(0.158)	(0.174)	(0.184)	(0.187)	(0.192)
	R^2	0.060	0.102	0.030	0.037	0.037	0.019	0.039	0.026	0.042	0.031
VS	a	4.236	-1.797	5.419	4.174	5.853	3.378	3.238	4.074	3.263	3.906
		(1.539)	(1.687)	(2.056)	(2.346)	(2.616)	(0.706)	(0.705)	(0.697)	(0.676)	(0.659)
	b	0.727	2.049	0.596	0.933	0.555	0.205	0.241	0.083	0.253	0.121
		(0.241)	(0.307)	(0.420)	(0.524)	(0.624)	(0.110)	(0.115)	(0.118)	(0.117)	(0.117)
	R^2	0.024	0.109	0.005	0.009	0.002	0.009	0.012	0.001	0.013	0.003
		Italy					**France**				
GARCH	a	5.036	4.392	4.943	4.615	3.706	3.605	2.138	3.502	3.665	4.176
		(2.283)	(2.335)	(2.397)	(2.453)	(2.507)	(1.754)	(1.778)	(1.822)	(1.857)	(1.892)
	b	0.462	0.530	0.471	0.507	0.600	0.575	0.775	0.583	0.563	0.497
		(0.232)	(0.238)	(0.245)	(0.251)	(0.257)	(0.219)	(0.224)	(0.231)	(0.236)	(0.242)
	R^2	0.011	0.013	0.010	0.011	0.015	0.019	0.032	0.017	0.015	0.012
GJR	a	6.200	5.650	5.741	5.577	4.576	2.667	1.145	2.929	3.202	4.211
		(2.248)	(2.305)	(2.368)	(2.430)	(2.489)	(1.725)	(1.750)	(1.808)	(1.851)	(1.899)
	b	0.344	0.405	0.395	0.414	0.520	0.712	0.928	0.682	0.644	0.509
		(0.233)	(0.240)	(0.248)	(0.255)	(0.262)	(0.222)	(0.227)	(0.236)	(0.242)	(0.250)
	R^2	0.006	0.008	0.007	0.007	0.011	0.028	0.044	0.023	0.019	0.011
Q	a	5.349	4.744	5.189	4.911	3.930	3.214	1.975	3.558	4.083	4.826
		(2.303)	(2.362)	(2.429)	(2.494)	(2.555)	(1.628)	(1.661)	(1.721)	(1.771)	(1.823)
	b	0.436	0.502	0.454	0.485	0.588	0.638	0.814	0.596	0.522	0.425
		(0.238)	(0.245)	(0.253)	(0.261)	(0.268)	(0.208)	(0.213)	(0.222)	(0.230)	(0.238)
	R^2	0.009	0.011	0.009	0.009	0.013	0.025	0.039	0.019	0.014	0.009
VS	a	9.278	9.115	9.551	9.139	7.920	5.068	0.814	6.672	4.661	10.715
		(0.861)	(0.932)	(1.155)	(1.730)	(2.671)	(1.871)	(2.133)	(2.450)	(2.678)	(2.819)
	b	0.001	0.019	-0.040	0.023	0.240	0.510	1.378	0.253	0.708	-0.647
		(0.023)	(0.052)	(0.118)	(0.254)	(0.470)	(0.320)	(0.401)	(0.496)	(0.573)	(0.631)
	R^2	0.000	0.000	0.000	0.000	0.001	0.007	0.032	0.001	0.004	0.003

Table 6. Mincer-Zarnowitz regression (continued)

		Spain					Portugal				
Model	h	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
GARCH	a	2.321	1.441	2.474	2.719	1.798	2.481	2.615	4.334	4.536	4.592
		(1.177)	(1.185)	(1.226)	(1.251)	(1.255)	(1.168)	(1.187)	(1.230)	(1.242)	(1.251)
	b	0.667	0.810	0.651	0.617	0.756	0.590	0.565	0.312	0.280	0.271
		(0.142)	(0.144)	(0.150)	(0.154)	(0.156)	(0.104)	(0.106)	(0.110)	(0.110)	(0.111)
	R^2	0.060	0.083	0.051	0.044	0.063	0.084	0.075	0.023	0.018	0.017
GJR	a	2.065	0.765	2.056	1.986	0.671	3.304	3.104	5.313	5.329	5.427
		(1.156)	(1.161)	(1.220)	(1.252)	(1.261)	(1.202)	(1.212)	(1.249)	(1.257)	(1.264)
	b	0.718	0.932	0.734	0.751	0.960	0.475	0.502	0.176	0.173	0.159
		(0.140)	(0.144)	(0.153)	(0.160)	(0.164)	(0.109)	(0.110)	(0.114)	(0.114)	(0.115)
	R^2	0.070	0.108	0.061	0.059	0.089	0.051	0.056	0.007	0.006	0.005
Q	a	2.131	1.010	2.129	2.197	1.099	2.650	2.711	4.494	4.752	4.856
		(1.160)	(1.167)	(1.218)	(1.248)	(1.257)	(1.131)	(1.150)	(1.192)	(1.205)	(1.213)
	b	0.708	0.893	0.720	0.714	0.885	0.558	0.542	0.266	0.237	0.227
		(0.141)	(0.144)	(0.152)	(0.158)	(0.161)	(0.104)	(0.107)	(0.111)	(0.112)	(0.113)
	R^2	0.067	0.099	0.060	0.055	0.079	0.073	0.066	0.016	0.012	0.011
VS	a	3.257	-0.621	1.257	-0.286	-3.803	2.088	0.439	4.278	4.903	4.466
		(1.139)	(1.185)	(1.382)	(1.536)	(1.658)	(1.103)	(1.147)	(1.355)	(1.499)	(1.647)
	b	0.792	1.987	1.687	2.402	3.906	0.802	1.277	0.528	0.421	0.585
		(0.203)	(0.260)	(0.362)	(0.462)	(0.557)	(0.115)	(0.154)	(0.225)	(0.297)	(0.372)
	R^2	0.042	0.143	0.059	0.072	0.123	0.123	0.165	0.015	0.006	0.007

		Japan				
Model	h	**1**	**2**	**3**	**4**	**5**
GARCH	a	1.689	1.743	1.768	1.630	2.007
		(0.458)	(0.459)	(0.458)	(0.454)	(0.459)
	b	0.336	0.309	0.292	0.327	0.202
		(0.097)	(0.094)	(0.091)	(0.087)	(0.085)
	R^2	0.035	0.032	0.030	0.041	0.017
GJR	a	1.222	1.268	1.376	1.087	1.702
		(0.434)	(0.443)	(0.454)	(0.455)	(0.477)
	b	0.593	0.597	0.570	0.720	0.453
		(0.104)	(0.113)	(0.123)	(0.131)	(0.145)
	R^2	0.090	0.078	0.061	0.084	0.029
Q	a	3.086	3.326	3.147	2.912	3.023
		(0.406)	(0.458)	(0.427)	(0.355)	(0.384)
	b	0.000	0.000	0.000	0.000	0.000
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.000	0.000	0.002	0.008	0.003
VS	a	0.594	0.689	1.254	0.959	1.950
		(0.432)	(0.446)	(0.473)	(0.480)	(0.509)
	b	0.881	1.043	0.912	1.339)	0.672
		(0.114)	(0.149)	(0.200)	(0.253)	(0.332)
	R^2	0.154	0.129	0.060	0.078	0.012

Table 6. Mincer-Zarnowitz regression (continued)

		Switzerland					Greece				
Model	*h*	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
GARCH	*a*	2.403	2.245	3.965	3.903	3.778	16.267	15.951	14.134	9.855	16.867
		(1.170)	(1.174)	(1.212)	(1.218)	(1.224)	(4.024)	(4.328)	(4.650)	(4.960)	(5.341)
	b	0.658	0.688	0.407	0.426	0.447	0.185	0.197	0.268	0.437	0.151
		(0.133)	(0.135)	(0.140)	(0.142)	(0.143)	(0.128)	(0.143)	(0.157)	(0.169)	(0.183)
	R^2	0.068	0.072	0.024	0.026	0.028	0.006	0.006	0.009	0.020	0.002
GJR	*a*	1.904	1.431	3.696	3.440	3.252	17.506	17.752	15.889	10.922	16.346
		(1.178)	(1.188)	(1.251)	(1.269)	(1.289)	(3.539)	(3.848)	(4.198)	(4.576)	(5.059)
	b	0.735	0.823	0.454	0.509	0.545	0.122	0.114	0.185	0.378	0.165
		(0.135)	(0.140)	(0.151)	(0.156)	(0.162)	(0.093)	(0.110)	(0.128)	(0.146)	(0.166)
	R^2	0.081	0.093	0.026	0.030	0.032	0.005	0.003	0.006	0.020	0.003
Q	*a*	2.271	1.972	3.889	3.618	3.551	17.567	17.051	16.074	11.447	12.856
		(1.201)	(1.210)	(1.254)	(1.265)	(1.278)	(3.924)	(4.316)	(4.743)	(5.142)	(5.546)
	b	0.665	0.717	0.408	0.460	0.471	0.124	0.148	0.190	0.385	0.324
		(0.137)	(0.140)	(0.147)	(0.150)	(0.153)	(0.121)	(0.144)	(0.166)	(0.185)	(0.203)
	R^2	0.065	0.072	0.022	0.027	0.027	0.003	0.003	0.004	0.013	0.008
VS	*a*	1.112	-1.130	2.802	1.736	0.353	13.728	14.970	14.533	14.315	13.135
		(1.245)	(1.285)	(1.477)	(1.602)	(1.752)	(4.153)	(4.238)	(4.316)	(4.396)	(4.472)
	b	1.015	1.639	0.875	1.255	1.754	0.208	0.178	0.202	0.219	0.273
		(0.177)	(0.217)	(0.290)	(0.358)	(0.439)	(0.100)	(0.109)	(0.117)	(0.126)	(0.134)
	R^2	0.089	0.145	0.026	0.035	0.045	0.013	0.008	0.009	0.009	0.012
		China					**Singapore**				
Model	*h*	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
GARCH	*a*	1.091	1.143	1.169	1.233	1.255	0.487	0.912	1.145	1.551	1.249
		(0.276)	(0.272)	(0.267)	(0.262)	(0.257)	(0.393)	(0.502)	(0.591)	(0.651)	(0.683)
	b	0.144	0.105	0.082	0.049	0.036	0.786	0.531	0.395	0.145	0.327
		(0.078)	(0.065)	(0.054)	(0.044)	(0.034)	(0.173)	(0.256)	(0.320)	(0.360)	(0.381)
	R^2	0.010	0.008	0.007	0.004	0.003	0.059	0.013	0.005	0.000	0.002
GJR	*a*	1.155	1.160	1.168	1.227	1.271	1.049	1.073	0.995	1.084	0.321
		(0.256)	(0.257)	(0.257)	(0.256)	(0.250)	(0.306)	(0.376)	(0.506)	(0.684)	(0.829)
	b	0.108	0.097	0.084	0.053	0.031	0.436	0.437	0.502	0.450	0.937
		(0.060)	(0.055)	(0.049)	(0.043)	(0.032)	(0.088)	(0.159)	(0.267)	(0.399)	(0.499)
	R^2	0.010	0.009	0.009	0.005	0.003	0.070	0.023	0.011	0.004	0.011
Q	*a*	1.043	1.064	1.103	1.163	1.185	1.276	2.008	1.981	2.072	2.061
		(0.275)	(0.264)	(0.271)	(0.267)	(0.263)	(0.368)	(0.291)	(0.271)	(0.315)	(0.285)
	b	0.169	0.133	0.121	0.078	0.065	0.296	-0.001	0.000	0.000	0.000
		(0.081)	(0.069)	(0.063)	(0.054)	(0.047)	(0.081)	(0.004)	(0.000)	(0.000)	(0.000)
	R^2	0.013	0.011	0.011	0.006	0.006	0.039	0.000	0.001	0.000	0.000
VS	*a*	1.246	1.246	1.215	1.212	1.276	0.521	0.270	0.335	0.397	-0.235
		(0.250)	(0.247)	(0.244)	(0.246)	(0.245)	(0.365)	(0.532)	(0.728)	(0.838)	(0.867)
	b	0.055	0.064	0.087	0.098	0.060	0.671	0.846	0.840	0.815	1.195
		(0.048)	(0.050)	(0.053)	(0.057)	(0.060)	(0.130)	(0.253)	(0.386)	(0.463)	(0.486)
	R^2	0.004	0.005	0.008	0.009	0.003	0.075	0.033	0.014	0.009	0.018

Notes to Table 6: *a* and *b* are Ordinary Least Squares estimates of the parameters in regression (16); standard errors calculated using the Newey-West correction are reported in parentheses.

Table 7. Weights of the forecast combination (constant coefficients)

	Holland					**Belgium**				
Model *h*	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Const.	1.448	-2.411	0.730	1.771	2.539	1.508	-4.417	0.924	1.565	0.172
GARCH	-2.386	-0.141	-1.383	-1.663	-1.448	-0.865	3.950	-0.260	-1.007	-0.761
GJR	-1.167	-0.791	-12.320	-6.799	-7.750	5.762	0.379	-1.204	0.441	-0.110
Q	4.043	1.284	14.221	8.937	9.837	-3.556	-5.321	1.150	0.798	0.789
VS	0.476	1.819	0.470	0.374	-0.258	-0.701	4.942	2.068	1.030	2.481
R^2	0.139	0.236	0.155	0.097	0.120	0.176	0.384	0.038	0.025	0.031
	Germany					**U.K.**				
Const.	3.845	-5.339	1.815	3.103	5.487	2.341	0.938	2.318	2.394	2.450
GARCH	-0.949	0.037	1.282	0.541	1.525	0.170	-0.023	-0.130	-0.031	0.276
GJR	3.531	1.770	0.365	1.727	2.076	0.030	0.020	0.990	1.827	1.712
Q	-1.846	-1.442	-1.456	-1.739	-3.190	0.460	0.692	-0.041	-0.801	-0.881
VS	-0.364	2.060	0.837	0.109	-0.334	-0.227	0.024	-0.411	-0.657	-0.800
R^2	0.097	0.206	0.026	0.038	0.053	0.031	0.055	0.062	0.115	0.101
	Italy					**France**				
Const.	6.155	4.928	6.204	5.365	4.398	-2.161	-6.794	-1.476	1.313	3.417
GARCH	0.721	1.029	1.391	0.801	0.530	-0.212	-0.268	-0.017	-0.636	-0.917
GJR	-0.802	-0.632	0.423	-0.130	-0.118	1.702	2.934	1.235	2.562	2.525
Q	0.481	0.107	-1.397	-0.078	0.402	-0.745	-1.746	-0.415	-1.116	-0.726
VS	0.000	0.025	-0.040	-0.130	-0.308	0.904	1.689	0.811	0.247	-0.345
R^2	0.012	0.017	0.010	0.014	0.021	0.075	0.119	0.051	0.043	0.046
	Spain					**Portugal**				
Const.	2.995	-2.194	1.223	-1.362	-6.802	3.244	0.325	7.738	7.994	7.271
GARCH	-1.535	0.795	-1.285	-1.344	-0.375	3.203	4.209	7.781	9.584	10.118
GJR	2.025	-1.691	-1.711	-2.373	-0.119	-7.768	0.393	-8.254	-4.487	-4.524
Q	0.573	0.780	3.492	3.780	0.343	4.902	-4.605	0.713	-5.004	-5.645
VS	-0.634	2.705	0.923	2.937	5.739	0.182	1.199	-0.777	-0.887	-0.624
R^2	0.090	0.184	0.087	0.112	0.192	0.284	0.214	0.281	0.209	0.220
	Switzerland					**Greece**				
Const.	2.126	-0.348	3.718	2.088	0.547	11.020	9.981	9.786	9.729	11.289
GARCH	1.007	0.827	1.081	0.158	0.330	0.454	1.308	1.585	0.516	-1.445
GJR	0.479	-0.264	-0.087	-0.210	-0.248	0.336	-0.349	-0.291	0.411	0.745
Q	-1.208	-0.704	-0.854	0.132	-0.141	-0.868	-0.824	-1.311	-0.809	0.702
VS	0.636	1.841	0.652	1.256	2.104	0.328	0.246	0.360	0.226	0.326
R^2	0.093	0.153	0.036	0.044	0.060	0.032	0.031	0.046	0.039	0.031
	China					**Singapore**				
Const.	1.020	0.683	1.027	1.173	1.128	0.769	0.241	0.932	1.502	1.250
GARCH	-1.401	-2.856	-0.919	-0.436	-0.359	0.626	0.698	1.279	0.637	-0.900
GJR	-0.114	-0.474	-0.147	-0.107	0.030	-0.226	-0.177	0.788	2.944	2.272
Q	1.864	3.917	1.336	0.684	0.564	0.304	-0.221	-0.412	-0.194	-0.158
VS	-0.073	-0.049	0.011	0.071	-0.108	-0.262	0.470	-0.927	-2.651	-0.730
R^2	0.127	0.092	0.086	0.091	0.086	0.135	0.068	0.098	0.077	0.055
	Japan									
Const.	0.489	1.185	1.297	0.820	1.186					
GARCH	0.172	-0.036	-0.112	-0.018	-0.013					
GJR	0.089	0.188	0.359	0.099	0.152					
Q	0.000	0.000	-1.040	0.000	0.000					
VS	0.063	-0.033	-0.187	0.384	0.011					
R^2	0.099	0.061	0.066	0.092	0.057					

Table 8. Forecast combination with constant weights and Mincer-Zarnowitz regression

					Holland						Belgium		
Model	*h*	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***
Comb.	1	0.914	1.230	0.995	1.109	0.858	0.571	1.046	1.124	1.059	1.063	0.095	0.089
	2	0.962	0.588	0.918	0.767	0.011	0.038	1.376	1.735	1.150	1.317	0.090	0.089
	3	1.008	1.304	1.028	1.142	0.559	0.131	1.050	1.120	0.965	1.058	0.569	0.705
	4	0.893	1.562	0.998	1.250	0.912	0.571	1.012	1.223	0.948	1.106	0.318	0.705
	5	1.004	1.445	1.061	1.202	0.151	0.038	1.008	1.096	0.959	1.047	0.554	0.450
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		2.271	2.099	3.424	2.233	3.759		3.554	4.297	1.262	-0.068	0.099	
		(0.533)	(0.624)	(0.312)	(0.457)	(0.204)		(1.401)	(1.243)	(2.445)	(2.619)	(2.651)	
b		1.743	1.395	1.268	1.488	1.278		0.476	0.306	0.964	1.187	1.164	
		(0.194)	(0.165)	(0.123)	(0.155)	(0.116)		(0.169)	(0.117)	(0.415)	(0.445)	(0.455)	
R^2		0.064	0.114	0.055	0.072	0.027		0.067	0.059	0.046	0.060	0.056	
					Germany						U.K.		
Model	*h*	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***
Comb.	1	1.210	0.708	0.977	0.841	0.661	0.059	0.979	0.621	0.918	0.788	0.004	0.000
	2	1.270	0.741	1.046	0.861	0.367	0.705	0.967	0.703	0.929	0.838	0.001	0.000
	3	0.968	0.727	0.913	0.853	0.010	0.001	0.915	0.717	0.905	0.847	0.006	0.014
	4	0.946	0.813	0.927	0.901	0.034	0.001	0.985	0.804	0.954	0.897	0.191	0.850
	5	1.023	0.761	0.977	0.872	0.565	0.257	0.979	0.979	0.987	0.989	0.918	0.089
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		13.909	10.147	2.296	0.047	4.242		8.828	4.018	1.421	4.507	3.710	
		(3.063)	(2.160)	(2.963)	(3.250)	(2.302)		(4.054)	(3.711)	(2.915)	(2.113)	(1.811)	
b		-0.327	0.083	0.877	1.076	0.530		0.655	0.324	0.796	0.179	0.283	
		(0.322)	(0.195)	(0.285)	(0.310)	(0.181)		(0.829)	(0.703)	(0.545)	(0.363)	(0.294)	
R^2		0.009	0.002	0.079	0.098	0.072		0.006	0.002	0.019	0.002	0.008	
					Italy						France		
Comb.	1	0.997	1.334	1.027	1.155	0.274	0.014	1.040	0.970	1.048	0.985	0.137	0.257
	2	0.992	1.137	1.024	1.066	0.375	0.005	1.087	1.272	1.101	1.128	0.027	0.186
	3	1.005	1.128	1.031	1.062	0.397	0.002	1.017	1.347	1.042	1.161	0.076	0.450
	4	1.003	1.385	1.039	1.177	0.184	0.002	0.984	1.245	1.022	1.116	0.511	0.571
	5	1.021	1.358	1.051	1.165	0.015	0.000	1.010	1.317	1.026	1.148	0.449	0.705
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		-8.324	-2.438	-2.161	0.010	1.670		9.936	7.446	10.587	7.452	22.382	
		(8.578)	(7.091)	(9.088)	(7.001)	(5.622)		(4.199)	(3.338)	(5.370)	(6.626)	(6.905)	
b		1.613	1.039	1.015	0.742	0.547		0.191	0.076	-0.273	0.069	-1.588	
		(0.839)	(0.691)	(0.902)	(0.664)	(0.515)		(0.430)	(0.308)	(0.566)	(0.719)	(0.767)	
R^2		0.032	0.020	0.011	0.011	0.010		0.002	0.001	0.002	0.000	0.037	

Table 8. Forecast combination with constant weights and Mincer-Zarnowitz regression (continued)

		Spain						Portugal					
Model	*h*	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***
Comb.	1	0.976	1.232	1.035	1.110	0.046	0.089	0.949	1.230	0.954	1.109	0.145	0.571
	2	1.079	0.957	1.059	0.978	0.245	0.450	1.248	1.119	1.145	1.057	0.006	0.008
	3	1.004	1.643	1.090	1.282	0.016	0.008	1.057	1.954	1.081	1.398	0.131	0.059
	4	1.197	1.772	1.182	1.331	0.011	0.005	1.282	2.348	1.185	1.532	0.008	0.008
	5	1.397	1.434	1.247	1.197	0.011	0.005	1.358	2.245	1.202	1.498	0.026	0.001
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		5.395	5.104	5.817	8.142	7.211		2.921	5.393	6.335	9.762	9.739	
		(2.897)	(1.709)	(2.547)	(1.988)	(1.528)		(2.170)	(1.348)	(3.302)	(2.087)	(1.693)	
b		0.135	0.191	0.114	-0.135	-0.025		0.432	0.021	-0.139	-0.629	-0.649	
		(0.389)	(0.186)	(0.292)	(0.197)	(0.135)		(0.357)	(0.180)	(0.478)	(0.277)	(0.226)	
R^2		0.001	0.009	0.001	0.004	0.000		0.013	0.000	0.001	0.045	0.069	
		Switzerland						**Greece**					
Comb.	1	1.007	2.151	1.105	1.468	0.000	0.000	0.951	0.500	0.877	0.707	0.001	0.008
	2	0.989	2.016	1.136	1.420	0.001	0.000	0.965	0.591	0.901	0.769	0.002	0.002
	3	0.993	2.593	1.145	1.610	0.001	0.000	1.005	0.542	0.921	0.737	0.047	0.014
	4	1.001	2.329	1.169	1.526	0.006	0.000	0.990	0.490	0.871	0.700	0.000	0.000
	5	1.122	2.724	1.272	1.651	0.000	0.000	0.973	0.362	0.872	0.601	0.002	0.000
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		-1.701	-0.009	8.401	7.216	10.195		11.910	25.296	32.050	43.502	17.077	
		(2.164)	(1.838)	(3.531)	(3.631)	(3.481)		(10.670)	(14.924)	(12.526)	(18.767)	(11.816)	
b		0.939	0.648	-0.529	-0.337	-0.669		0.517	-0.049	-0.305	-0.781	0.386	
		(0.309)	(0.235)	(0.487)	(0.466)	(0.410)		(0.411)	(0.577)	(0.478)	(0.809)	(0.477)	
R^2		0.077	0.064	0.011	0.005	0.023		0.014	0.000	0.004	0.008	0.006	
		China						**Singapore**					
Comb.	1	0.868	1.110	0.958	1.054	0.055	0.686	0.925	1.833	1.116	1.354	0.030	0.419
	2	0.953	0.944	0.985	0.971	0.568	0.840	0.891	0.585	0.861	0.765	0.024	0.009
	3	0.883	1.206	0.943	1.098	0.057	0.686	2.189	2.008	1.546	1.417	0.001	0.000
	4	0.911	1.285	0.970	1.133	0.009	0.686	3.629	4.256	2.094	2.063	0.000	0.000
	5	0.951	1.063	0.948	1.031	0.230	0.544	8.308	1.596	1.570	1.263	0.182	0.000
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		0.592	0.685	0.281	-0.119	1.919		0.856	1.170	1.197	1.319	1.137	
		(0.662)	(0.334)	(0.840)	(1.503)	(1.281)		(0.664)	(0.488)	(0.319)	(0.345)	(0.279)	
b		0.332	0.279	0.566	0.819	-0.687		0.147	-0.016	-0.023	-0.050	0.012	
		(0.485)	(0.226)	(0.617)	(1.066)	(0.980)		(0.309)	(0.325)	(0.081)	(0.063)	(0.034)	
R^2		0.005	0.015	0.009	0.006	0.005		0.002	0.000	0.001	0.006	0.001	
		Japan											
Comb.	1	0.838	0.520	0.752	0.721	0.068	0.000						
	2	0.789	0.828	0.816	0.910	0.032	0.106						
	3	0.754	0.838	0.797	0.915	0.091	0.686						
	4	0.781	0.743	0.799	0.862	0.217	0.026						
	5	0.676	0.719	0.737	0.848	0.113	0.419						
	h	**1**	**2**	**3**	**4**	**5**							
a		0.192	5.269	2.754	2.796	1.807							
		(0.882)	(3.502)	(1.961)	(1.287)	(3.785)							
b		1.045	-3.043	-1.160	-1.164	-0.487							
		(0.851)	(2.621)	(1.435)	(0.910)	(2.691)							
R^2		0.015	0.014	0.007	0.017	0.000							

Notes to Table 8: Each section is relative to a specific stock index and it is divided in two parts. The upper part is devoted to forecast evaluation, while the lower part is dedicated to the Mincer-Zarnowitz regression.

Table 9. Rolling windows for forecast combination with variable weights

Stock market	Size of the rolling window
Holland	35 weekly obs.
Belgium	20 weekly obs.
Germany	15 weekly obs.
U.K.	25 weekly obs.
Italy	25 weekly obs.
France	35 weekly obs.
Spain	35 weekly obs.
Portugal	25 weekly obs.
Switzerland	20 weekly obs.
Greece	15 weekly obs.
China	20 weekly obs.
Singapore	25 weekly obs.
Japan	35 weekly obs.

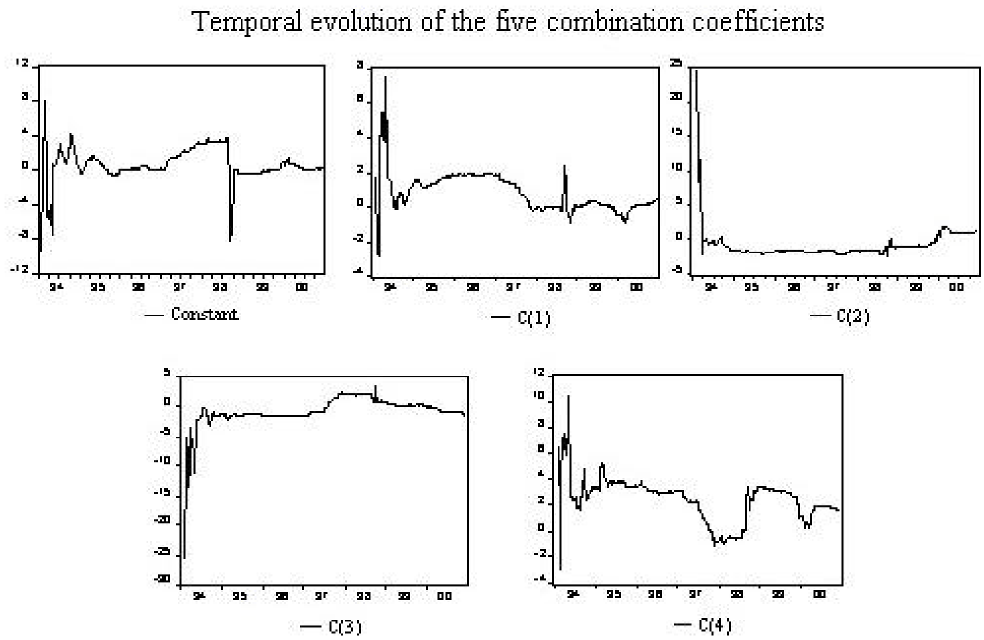

Figure 1. Temporal evolution of the five combination coefficients (constant included) relative to the 5-step-ahead forecasts for Italy.

Table 10. Forecast combination with variable weights and Mincer-Zarnowitz regression

		Holland						Belgium					
Model	h	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***
Comb.	1	1.118	1.203	1.325	1.097	0.003	0.741	2.048	1.325	1.330	1.135	0.067	0.000
	2	1.166	1.214	1.268	1.102	0.252	0.036	2.771	1.275	1.395	1.132	0.000	0.000
	3	1.116	1.317	1.299	1.148	0.185	0.271	1.658	1.173	1.137	1.172	0.094	0.076
	4	1.259	1.118	1.151	1.057	0.474	0.078	0.949	0.921	1.182	1.149	0.053	0.046
	5	1.287	1.470	1.320	1.213	0.298	0.099	0.990	0.853	0.920	1.005	0.138	0.419
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		2.474	2.415	2.392	2.383	2.530		1.160	1.688	1.055	1.816	2.909	
		(0.708)	(0.707)	(0.700)	(0.759)	(0.700)		(0.556)	(0.511)	(0.562)	(0.580)	(0.559)	
b		0.030	0.045	0.056	0.050	0.020		0.014	0.262	0.006	0.041	0.036	
		(0.043)	(0.041)	(0.038)	(0.060)	(0.036)		(0.011)	(0.027)	(0.017)	(0.027)	(0.021)	
R^2		0.111	0.124	0.026	0.082	0.038		0.095	0.212	0.033	0.097	0.129	
		Germany						**U.K.**					
Comb.	1	0.972	0.951	1.292	0.862	0.063	0.008	1.135	0.963	1.159	0.981	0.001	0.329
	2	1.033	1.030	1.367	0.937	0.032	0.200	1.139	1.187	1.198	1.090	0.000	0.129
	3	1.271	1.197	1.029	1.124	0.118	0.000	1.278	1.138	1.187	1.067	0.001	0.828
	4	1.302	0.949	0.973	1.131	0.137	0.000	1.203	0.911	1.188	0.954	0.000	0.193
	5	1.287	0.926	1.718	1.388	0.051	0.003	1.251	1.128	1.206	1.062	0.003	0.193
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		2.363	2.945	2.153	3.993	7.963		2.561	2.966	1.894	1.455	1.864	
		(0.889)	(0.920)	(0.898)	(0.905)	(0.934)		(0.471)	(0.503)	(0.522)	(0.525)	(0.503)	
b		0.011	0.090	0.005	0.016	0.027		0.239	0.119	0.131	0.006	0.117	
		(0.006)	(0.033)	(0.008)	(0.011)	(0.026)		(0.070)	(0.074)	(0.078)	(0.080)	(0.066)	
R^2		0.110	0.061	0.021	0.137	0.043		0.034	0.017	0.018	0.011	0.079	

Table 10. Forecast combination with variable weights and Mincer-Zarnowitz regression (continued)

		Spain						Portugal					
Model	*h*	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***	***MSPE***	***MedSPE***	***MAPE***	***MedAPE***	***DM***	***S***
Comb.	1	1.259	1.078	1.008	1.038	0.010	0.091	1.357	1.351	1.195	1.162	0.005	0.223
	2	1.109	0.801	1.040	0.895	0.035	0.736	1.429	1.048	1.220	1.024	0.199	0.268
	3	0.921	1.088	0.924	1.043	0.054	0.144	1.591	1.123	1.150	1.060	0.079	0.506
	4	0.917	1.123	0.937	1.106	0.030	0.368	1.938	1.087	1.201	1.043	0.026	0.438
	5	1.507	1.195	1.136	1.138	0.135	0.500	1.824	1.007	1.326	1.003	0.265	0.376
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		2.304	2.962	2.108	2.110	3.116		2.933	2.570	2.633	2.721	2.102	
		(0.846)	(0.893)	(0.876)	(0.989)	(0.855)		(1.016)	(0.992)	(1.093)	(1.052)	(1.039)	
b		0.095	-0.034	-0.012	0.081	0.045		0.144	0.122	0.170	0.174	0.132	
		(0.035)	(0.055)	(0.043)	(0.087)	(0.046)		(0.027)	(0.020)	(0.051)	(0.041)	(0.032)	
R^2		0.022	0.017	0.020	0.026	0.009		0.083	0.098	0.032	0.053	0.050	

		Switzerland						Greece					
Comb.	1	1.896	1.244	1.165	1.116	0.043	0.057	1.292	1.334	0.963	1.155	0.155	0.115
	2	1.091	0.903	1.072	1.010	0.012	0.007	1.004	1.379	1.307	1.174	0.174	0.177
	3	1.239	1.014	1.069	1.309	0.047	0.002	1.125	1.565	1.261	1.251	0.071	0.368
	4	1.202	1.295	1.049	1.340	0.069	0.217	0.898	1.346	1.421	1.160	0.070	0.653
	5	1.255	1.269	1.767	1.212	0.053	0.217	1.095	0.950	1.456	0.975	0.279	0.301
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		1.356	2.693	2.435	2.409	1.594		4.811	4.980	4.919	4.130	4.021	
		(0.928)	(0.961)	(0.948)	(0.953)	(0.944)		(1.796)	(1.803)	(1.812)	(1.767)	(1.798)	
b		0.036	0.008	0.023	0.030	0.012		-0.002	-0.001	0.000	-0.025	0.000	
		(0.018)	(0.043)	(0.024)	(0.026)	(0.024)		(0.004)	(0.003)	(0.009)	(0.009)	(0.001)	
R^2		0.162	0.081	0.044	0.034	0.020		0.001	0.001	0.000	0.022	0.001	

		China						Singapore					
Comb.	1	1.430	0.874	1.176	0.935	0.126	0.256	1.882	0.666	1.169	0.816	0.155	0.009
	2	1.092	0.758	1.010	0.871	0.689	0.140	3.767	0.579	1.544	0.761	0.022	0.004
	3	0.851	0.626	0.878	0.791	0.546	0.005	2.596	0.577	1.394	0.759	0.147	0.001
	4	0.773	0.500	0.855	0.707	0.392	0.000	3.141	0.614	1.309	0.783	0.222	0.006
	5	0.534	0.476	0.813	0.690	0.239	0.001	2.380	0.464	1.341	0.681	0.106	0.000
	h	**1**	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
a		1.266	1.287	1.332	1.258	1.381		1.617	1.811	1.804	1.793	1.833	
		0.251	0.245	0.243	0.244	0.257		0.296	0.291	0.294	0.300	0.297	
b		0.050	0.049	-0.005	0.067	-0.034		0.149	0.015	0.019	0.015	-0.010	
		0.054	0.062	0.071	0.052	0.060		0.054	0.034	0.045	0.038	0.049	
R^2		0.003	0.002	0.000	0.005	0.001		0.024	0.001	0.001	0.001	0.000	

		Japan					
Comb.	1	1.304	0.371	0.918	0.609	0.046	0.351
	2	2.053	0.432	1.058	0.657	0.176	0.080
	3	1.088	0.402	0.898	0.634	0.605	0.007
	4	0.946	0.351	0.842	0.593	0.552	0.004
	5	1.356	0.283	0.972	0.532	0.290	0.020
	h	**1**	**2**	**3**	**4**	**5**	
a		2.244	2.687	2.639	2.132	2.570	
		0.388	0.408	0.429	0.440	0.413	
b		0.319	0.027	0.069	0.386	0.046	
		0.051	0.050	0.127	0.146	0.069	
R^2		0.117	0.001	0.001	0.023	0.001	

Notes to Table 10: See notes to Table 8.

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