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THE IGARCH EFFECT: CONSEQUENCES ON VOLATILITY FORECASTING AND OPTION TRADING

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Abstract

This paper studies the integrated Garch (IGARCH) effect, a phenomenon often encountered when estimating conditional auto-regressive models on financial time series. The analysis of twelve indexes of major financial markets provides empirical evidence of its well-spread presence especially in periods of market turbulence. We examine its impact on volatility forecasting and on trading and hedging options. We show that a strong IGARCH effect may have relevant consequences on trading and on risk management.

JEL classification: C14, C16, C32.

Keywords and Phrases: stock returns, volatility forecasting, GARCH(1,1), IGARCH effect, option hedging

1. Introduction

The purpose of this paper is to investigate some of the possible consequences of the well known integrated Garch (IGARCH) effect. The IGARCH effect is often encountered when the parameters of a GARCH(1,1) model are estimated on the time series of a financial returns.

The GARCH(1,1) process is defined as

$$r_t = z_t h_t^{1/2}, \quad h_t = \alpha_0 + \alpha_1 \, r_{t-1}^2 + \beta_1 \, h_{t-1},$$

where z_t are i.i.d. with $Ez = 0$, $Ez^2 = 1$. The IGARCH effect is manifest when the sum of the coefficients α_1 and β_1 is statistically equal to one. This implies that the data generating process for the returns has an *infinite* second moment and that shocks have a *permanent* effect on volatility. This phenomenon, has a serious impact on volatility forecasts as current information remains relevant when forecasting the conditional variance for all horizons.

The IGARCH effect has been studied extensively in the econometric literature. In particular, a stream of papers that originates with Diebold (1986) analyzes its possible relation with the non-stationarity of the data. Mikosch and Stărică (2004) show theoretically that, at least in the frame of the Whittle estimation, the IGARCH effect can be due to the behavior of the estimators under mis-specification.

In this paper we perform an empirical investigation of stock indexes of twelve major financial markets (see Table 1) and study the volatility forecasting performance of the GARCH(1,1) model when affected by various degrees by the IGARCH effect. We empirically show that the IGARCH effect causes GARCH(1,1) to mis-estimate the unconditional variance. We identify periods of strong discrepancy between the estimated GARCH(1,1) unconditional volatility and the sample standard deviation *on most of the series* under scrutiny. Since we are interested in documenting the consequences of the IGARCH effect, for each series we focus on the sub-samples where the effect is most pronounced. For such samples we document particularly poor forecasting performance of the GARCH(1,1) model. On the other hand, on sub-samples not affected by the IGARCH effect, the longer-horizon volatility forecast performance of the GARCH(1,1) model may be considered satisfactory.

We are mainly concerned with the evaluation of the longer-horizon volatility forecasting performance of the GARCH(1,1) model. To this end, we compare the GARCH(1,1) forecaster with a simple forecasting approach which assumes the volatility locally constant. The first comparison uses MSE to measure the quality of the forecast. The forecasting horizon extends from one day to one business year. The second approach compares the financial consequences of using the two volatility forecasts for pricing and hedging of simple financial derivatives on indexes. The second analysis is motivated by the observation that "a natural criteria for choosing between any pair of competing methods to forecast the variance of the rate of return on an asset would be the expected incremental profit from replacing the lesser forecast with the better one", as stated by Engle et al. (1993). We compare the performances of two hypothetical traders who adopt different models for volatility forecasts. The two volatility forecasts from the first comparison are employed to determine the initial prices of the replicating portfolios of at-the-money options as well as the dynamic strategies to be followed in hedging. The trade is effectuated at a price that is the average between the two initial prices, with the trader who proposed the highest one taking the long side and the other one taking the short side. Although motivated by the same idea, our approach differs in many ways from that in Engle et al. (1993) and (1997) (see Section 3 for details), because we focus on evaluating the ability of two competing modeling methodologies to value a claim and then to follow a dynamic hedging strategy. The quality of the volatility forecasts of competing models is measured at the expiration.

The rest of paper is organized as follows: in Section 2 we define the IGARCH effect and analyze the twelve time series of stock market indexes. Section 3 investigates the performances of the GARCH(1,1) model, with an emphasis on sub-samples affected by the IGARCH effect. Its impact on volatility forecasting and option trading is evaluated. Section 4 concludes.

2. Changes in the unconditional volatility and the IGARCH effect

Researchers that model financial returns in the ARCH framework, often assume that the data generating process for the log return r_t is the stationary GARCH(1,1) model

$$r_t = z_t h_t^{1/2}, \quad h_t = \alpha_0 + \alpha_1 \, r_{t-1}^2 + \beta_1 \, h_{t-1}, \tag{2.1}$$

where (z_t) are iid, $Ez = 0$, $Ez^2 = 1$. Condition $\alpha_1 + \beta_1 < 1$ is necessary and sufficient for the process to be weakly stationary. If this condition is not fulfilled, the GARCH(1,1) process, if (strongly) stationary, has infinite variance.

The IGARCH effect consists in the sum $\alpha_1 + \beta_1$ being (slightly smaller and) close to one. Under the assumption that the returns have finite second moment, the unconditional variance of the GARCH(1,1) model (2.1) is given by

$$\sigma^2_{GARCH(1,1)} := \alpha_0/(1 - \alpha_1 - \beta_1). \tag{2.2}$$

Replacing the GARCH(1,1) coefficients in (2.2) with estimated values yields the estimated *Garch unconditional variance*, $\widehat{\sigma}^2_{GARCH(1,1)}$. Note that (2.2) implies that the stronger the IGARCH effect, i.e. the closer $\widehat{\alpha}_1 + \widehat{\beta}_1$ is to one, the larger the estimated GARCH(1,1) unconditional volatility becomes.

In the recent financial econometric literature, many authors (some of which were cited in the Introduction) have argued that there is a causal connection between the IGARCH effect and structural changes in the unconditional variance of returns. That is, estimating a Garch(1,1) model on a sample displaying non-stationary changes of the unconditional volatility, may induce a spurious IGARCH effect.

To measure the intensity of the IGARCH effect in the sample $[t-a,t]$, a GARCH(1,1) model is estimated using the quasi-ML estimation method. A sample size of $a = 2000$ is commonly assumed to be sufficient for a precise estimation of a GARCH(1,1) model. This is the sample size [1] that we use in the sequel analysis. Besides the statistical motivation, the choice of a window of length 2000 incorporates the belief, common in the econometric community, that return time series can be safely modeled by stationary models, i.e. the stochastic features of the data are relatively stable in time.

We denote by $\widehat{\sigma}_{GARCH(1,1)}\ (t)$ the estimated GARCH(1,1) unconditional sd of the sample $[t-a,t]$ and by $\widehat{\sigma}(t)$ that sample's sd $\widehat{\sigma}(t) := (\sum_{i=t-a}^{t} r_i^2)/a$. The strength of the IGARCH effect in the sample $[t-a,t]$ is measured by its impact on the estimation of the unconditional variance of that sample. A strong discrepancy between the two estimates of the standard deviation of the data as a clear indication that GARCH(1,1) fails to model the dynamics of the returns.

The data used in the study are daily returns on twelve stock market indexes from the major economies of the world. The sample periods are specified in Table 1.

In Figure 2.1 we display the sum $\widehat{\alpha}_1 + \widehat{\beta}_1$ for the twelve series, together with the upper one-sided 95% confidence intervals. Figure 2.2 displays the estimated GARCH(1,1) unconditional sd

[1] A sample size of 1000-1500 is the absolute minimum in terms of statistical precision of the estimated coefficients. See Straumann (2005).

	Index	Country	sub-sample	Full sample
1.	ASX	Australia	01/07/1995-05/06/2003	05/01/1985-26/05/2004
2.	ATX	Austria	07/01/1993-07/02/2001	07/01/1993-26/05/2004
3.	CAC 40	France	15/05/1995-23/04/2003	03/04/1990-15/04/2004
4.	FTSE 100	UK	21/04/1995-21/03/2003	06/05/1984-18/03/2004
5.	DAX	Germany	08/04/1995-21/03/2003	03/04/1990-17/03/2004
6.	OMX	Sweden	23/10/1994-25/10/2002	02/11/1986-18/04/2004
7.	Russell 3000	USA	16/09/1994-31/08/2002	07/01/1988-03/06/2004
8.	BEL 20	Belgium	13/01/1995-22/03/2003	05/01/1985-26/05/2004
9.	FAZ	Germany	24/03/1995-21/03/2003	07/09/1984-19/03/2004
10.	S&P/TSX	Canada	17/12/1994-01/12/2002	18/08/1984-18/03/2004
11.	NIKKEI 225	Japan	01/12/1985-21/01/1994	09/02/1984-18/03/2004
12.	DJI	USA	06/11/1994-16/10/2002	02/01/1988-18/04/2004

TABLE 1. Samples of index returns. The full sample is used in the analysis in Section 2. The dates in the second column (sub-sample) correspond to 2000 observations used in evaluating volatility forecasting in Section 3.

together with the sample sd (the parameters are re-estimated every 50 days). A comparison of the two figures brings visual evidence that the periods affected by IGARCH effect coincide with those of major departure between the two estimates of the unconditional variance, for all of the series under scrutiny.

From Figure 2.1 we observe that sub-samples with a particularly pronounced IGARCH effect are present in most of the twelve time series. A more refined analysis divides the twelve indexes in two groups. The first three time series from Table 1, i.e. ASX, ATX, CAC 40 indexes, are characterized by the absence of the IGARCH effect. The upper 95% confidence bound is strictly smaller than 1, the point estimate $\widehat{\alpha}_1 + \widehat{\beta}_1$ is significantly different from one. Moreover, in Figure 2.2 we see a good match between the estimated GARCH(1,1) unconditional variance $\widehat{\sigma}_{GARCH(1,1)}\ (t)$ and the sample variance $\widehat{\sigma}(t)$. All the remaining series display periods in which the point estimate $\widehat{\alpha}_1 + \widehat{\beta}_1$ is not significantly different from one. As a consequence, $\widehat{\sigma}_{GARCH(1,1)}\ (t)$ and $\widehat{\sigma}(t)$ often display relevant differences. Note that for the indexes FAZ, S&P/TSX and NIKKEI 225 (series 9, 10 and 11), the sum of the coefficient is sometimes practically equal to one and the corresponding estimated GARCH(1,1) unconditional variance consequently explodes.

Since for the model (2.1) the volatility forecast at longer horizons is, practically, the unconditional variance (see equation (3.1)), poor point estimates for this last quantity will, most likely, have a strong impact on the longer horizon volatility forecasting performance of the model. To substantiate this conjecture in the next section we analyze the forecasting performance of the GARCH(1,1) model on sub-samples that are characterized by a strong IGARCH effect. The sub-samples have been chosen to cover the periods such that the GARCH(1,1) estimate of the unconditional variance $\widehat{\sigma}_{GARCH(1,1)}\ (t)$ exhibits the most significant divergence from the sample variance $\widehat{\sigma}(t)$. The vertical lines in Figure 2.2 mark the right end of the sub-samples of length 2000 days employed for the analysis of the forecasts of future volatility in Section 3.

It is worth noticing that eleven of the twelve sub-samples analyzed cover a eight year period between 1995 and 2004 with only one other, i.e. the NIKKEI 250 covering the period 1985-1994 interval[2].

[2]The choice of the periods, i.e. full samples, intentionally covers the last decade of the last century for the Western nations and the period between mid 80's to mid 90's for Japan. These period were characterized by strong variations in the variance of returns (for the Western economies an extremely low volatility period in the middle of the 90's followed by a strongly volatile interval that ended with the end of the last bear market).

We believe that the fact that the selected sub-samples coincide with the known intervals of stock market upheaval (the end of the 90's for the Western stock markets and the end of the 80's and the beginning of the 90's for the Japanese stock market) is not a coincidence. It is in fact precisely during these turbulent intervals, characterized by relevant changes in the unconditional variance, that the Garch(1,1) model performs poorly.

3. Practical implications of the IGARCH effect

This section is devoted to the analysis of possible practical implications of the IGARCH effect. Towards this end we evaluate the volatility forecasting performance of the GARCH(1,1) model on the sub-samples specified in Table 1. As mentioned already, these sub-samples are among the ones in which the IGARCH effect is the strongest. The dotted vertical bars in Figures 2.2 mark the end of the sub-samples analyzed.

Under the assumption of a GARCH(1,1) data generating process (2.1) that satisfies $\alpha_1+\beta_1 < 1$, the minimum Mean Square Error (MSE) forecast at time t for r^2_{t+p} is

$$\sigma^{2,\,GARCH}_{t+p} := E_t r^2_{t+p} = \sigma^2_{GARCH(1,1)} + (\alpha_1+\beta_1)^{p-1}(h_t - \sigma^2_{GARCH(1,1)}), \tag{3.1}$$

where $\sigma^2_{GARCH(1,1)}$ is the unconditional variance defined in (2.2). Consequently, the minimum MSE forecast for the variance of the cumulative return over the next p days, is given by

$$\overline{\sigma}^{2,\,GARCH}_{t,p} \quad := \quad E_t(r_{t+1}+\ldots+r_{t+p})^2 = \sigma^{2,\,GARCH}_{t+1} + \cdots + \sigma^{2,\,GARCH}_{t+p}.$$

From Equation (3.1) it follows that, for large p, the forecast $\sigma^{2,\,GARCH}_{t+p}$ is close to the unconditional variance, $\sigma^2_{GARCH(1,1)}$. Therefore, failing to produce accurate point estimates for this last quantity will, most likely, produce poor longer horizon volatility forecasts. Stărică (2003) showed that for

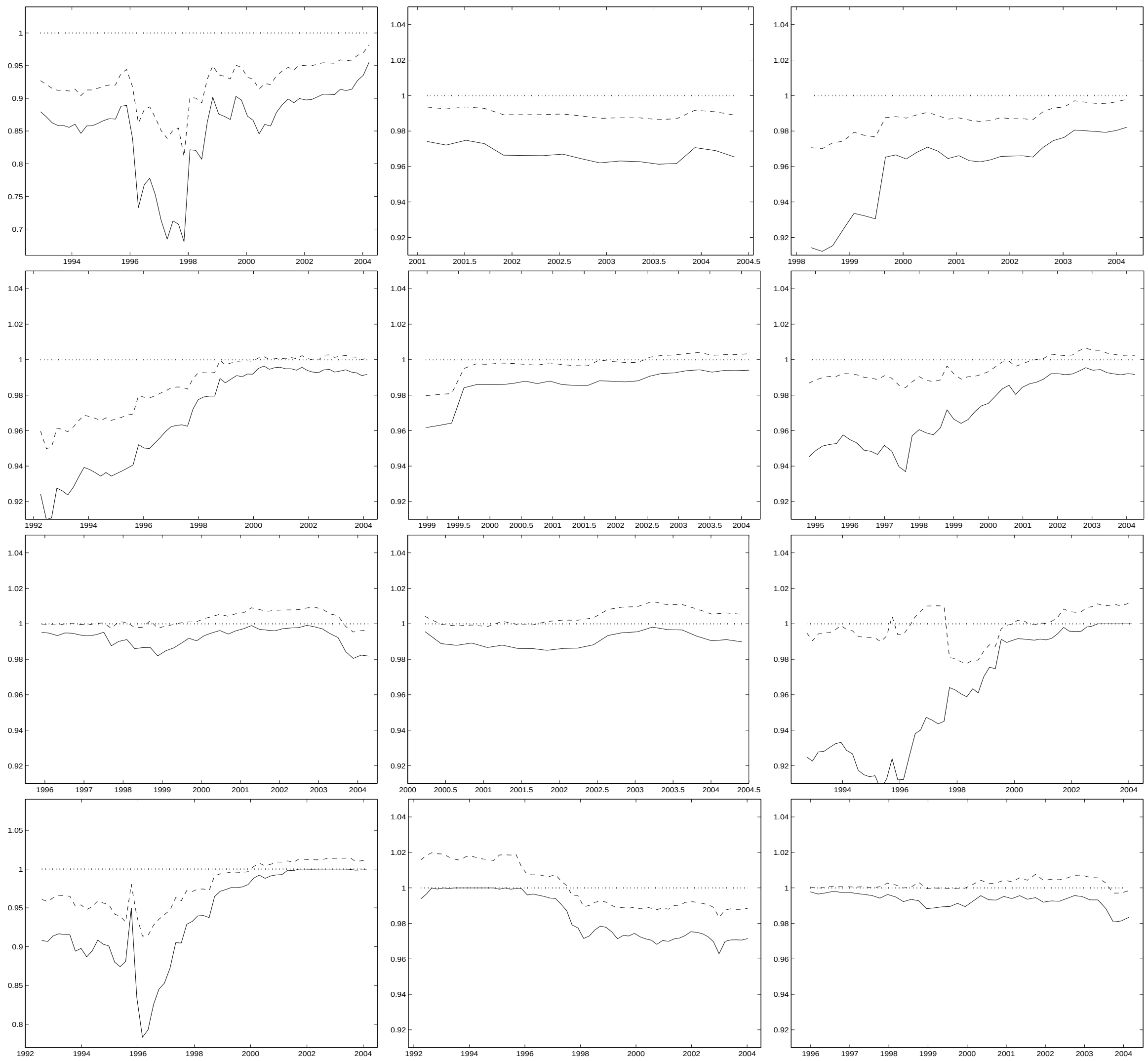

Figure 2.1. The sum $\widehat{\alpha}_1 + \widehat{\beta}_1$ (full line) with the upper one-sided 95% confidence interval (dotted) for the series in Table 1. The order from top-left to bottom-right corresponds to that in the table.

sub-samples of returns on the S&P500 index characterized by IGARCH effect, the GARCH(1,1) model fails to provide sensible longer-horizon volatility forecasts. In the sequel we bring further empirical evidence supporting this finding.

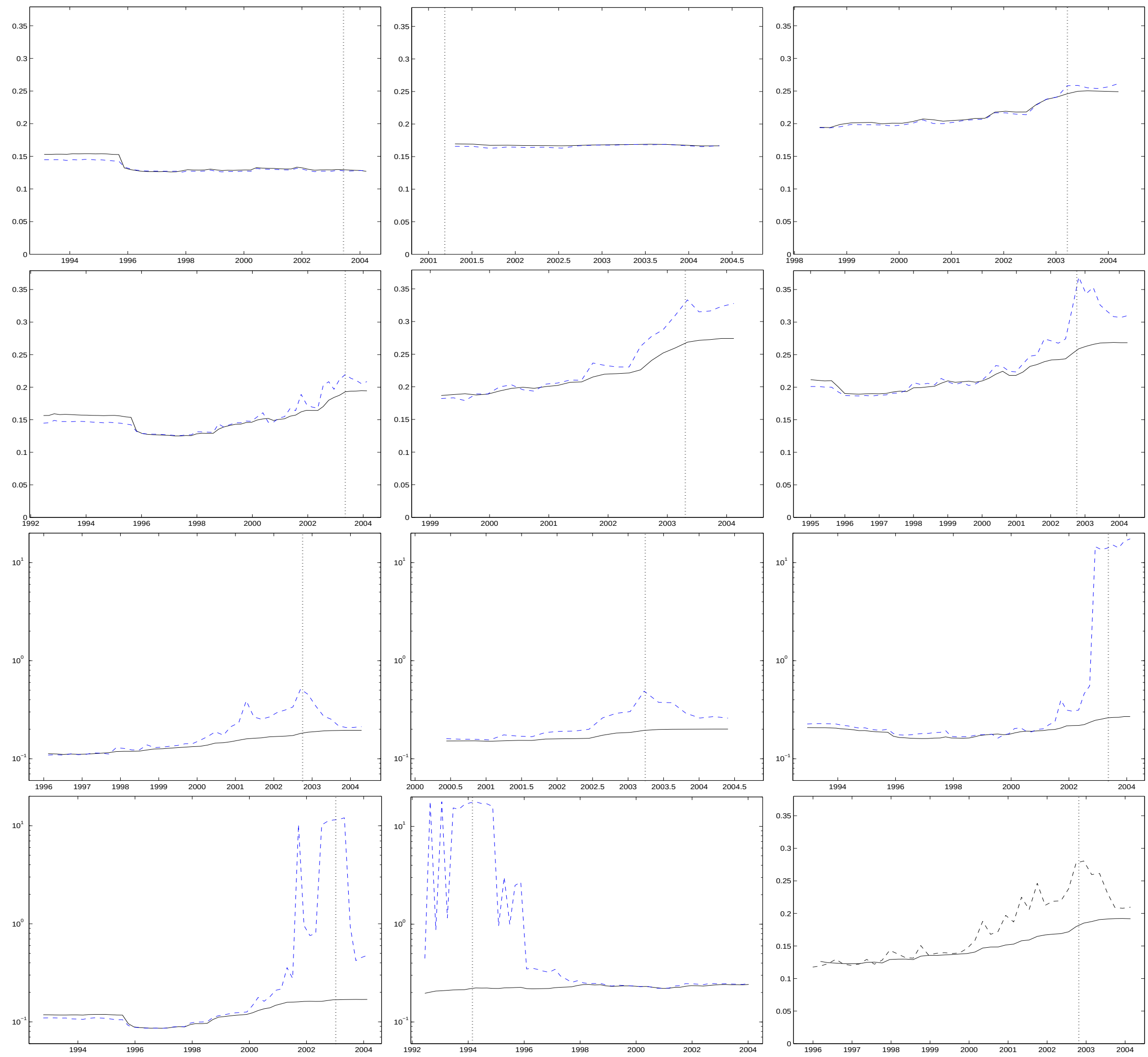

Figure 2.2. The sample sd (full line) and the GARCH(1,1) estimated sd (dotted) for the series in Table 1. The order from top-left to bottom-right corresponds to that in the table. The vertical lines mark the right end of the sub-samples of length 2000 days employed for the analysis of the forecasts of future volatility in Section 3.

The study of the implications of the IGARCH effect is based on a a direct comparison of the GARCH(1,1) forecaster with a simple forecasting approach which assumes that the volatility is locally constant[3]. Two different approaches are used. The first one compares the performance of the two forecasters in terms of the Mean Square Error while the second one looks at the profits and losses of two competing trading strategies based on the two forecasters.

3.1. **Volatility forecasts.** This subsection describes the set-up for direct evaluation of short- and longer-horizon volatility forecasting performance of a GARCH(1,1) model.

The benchmark model (BM) for volatility forecasting is the sample variance of the previous year of returns as the estimate for $\sigma^2(t)$. The forecast is then given by

$$\sigma^{2,\,BM}_{t+p} := \widehat{\sigma}^2_{250}(t) = \frac{1}{250}\sum_{i=1}^{250} r^2_{t-i+1}. \tag{3.2}$$

The forecast for the variance of the next p aggregated returns is then, simply,

$$\overline{\sigma}^{2,\,BM}_{t,p} := p\,\widehat{\sigma}^2_{250}(t). \tag{3.3}$$

To measure the realized volatility in the interval [t+1, t+p] we define

$$\overline{r}^{\,2}_{t,p} := \sum_{i=1}^{p} r^2_{t+i}, \tag{3.4}$$

moreover, we compare the following MSE on n forecasts performed,

$$MSE^*(p) := \sum_{t=1}^{n}(\overline{r}^{\,2}_{t,p} - \overline{\sigma}^{2,\,*}_{t,p})^2 \tag{3.5}$$

where "$*$", here and in the sequel, stands for "BM" or "GARCH". The MSE (3.5) is preferred to the simpler MSE

$$\sum_{t=1}^{n}(r^2_{t+p} - \sigma^{2,\,*}_{t+p})^2$$

[3]The two forecasters are based on two very different modeling assumptions: one is a stationary modeling of the conditional variance while the other is a non-stationary description of the unconditional variance.

since this last one uses a poor measure of the realized return volatility. It is well known (see Andersen and Bollerslev [1]) that the realized square returns are poor estimates of the day-by-day movements in volatility, as the idiosyncratic component of daily returns is large. Through averaging some of the idiosyncratic noise in the daily squared return data is canceled yielding (3.4), a better measure against which to check the quality of the two forecasts.

The direct comparison of short- and longer-horizon volatility forecasts was performed on the twelve sub-samples of length 2000 reported in Table 1. The GARCH(1,1) model is estimated initially on the first 1000 data points from every sample. Consistent with the assumption of stationarity, fundamental to the ARCH methodology, the model is re-estimated every week (i.e. every 5 days) using the observations from the beginning of the sample up to the moment of re-estimation. At the same time, $\hat{\sigma}^2_{250}(t)$ is also estimated. After every re-estimation, volatility forecasts are made for the next year ($p = 1, \ldots, 250$) using (3.2) and (3.3). Following the out-of-sample forecasting paradigm, the quantities $MSE^{GARCH}(p)$ and $MSE^{BM}(p)$ defined in (3.5) are calculated based on the observations from the year that followed. The graphs in Figure 3.1 display the ratio $MSE^{BM}(p)/MSE^{GARCH}(p)$. A ratio smaller than one at horizon p indicates that the volatility forecast of the GARCH(1,1) parametric, conditional methodology for the interval of next p days is poorer than that based on the simple approach that assumes that the history of the past year will repeat. Figure 3.1 demonstrates strong variation in the quality of the GARCH(1,1) forecast. The first two graphs demonstrate an overall good performance at all forecasting horizons. The third and the fourth show only good shorter-horizon performance, with a deterioration of the quality of forecast at horizons beyond three or four months. For the rest of the sub-samples (from five to twelve) and for periods as long as four business years, the GARCH(1,1) model provides poor shorter- and longer- volatility forecasts (sometimes with exceptions of forecasts of

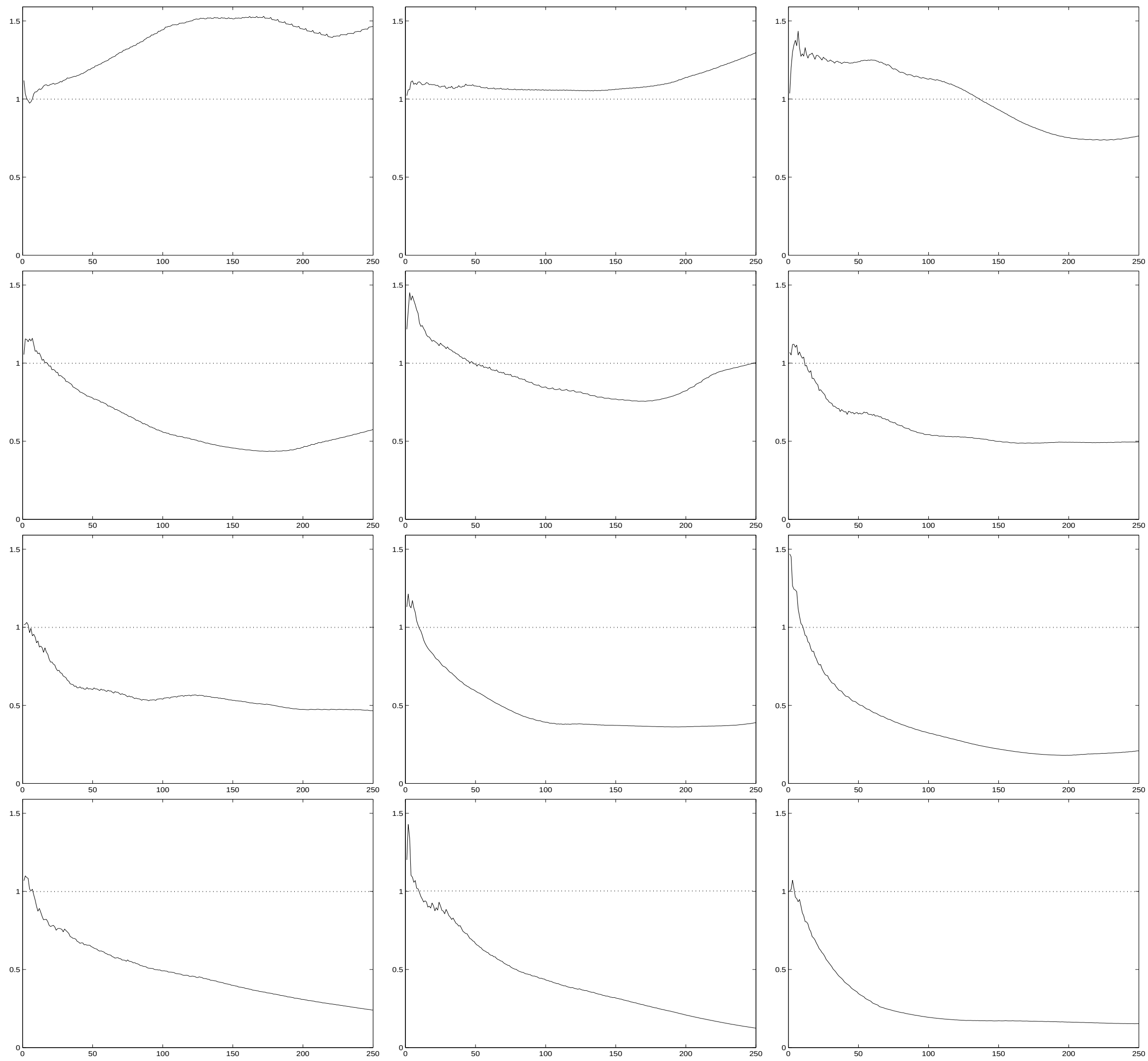

Figure 3.1. The ratio $MSE^{BM}(p)/MSE^{GARCH}(p)$ defined in (3.5) for the sub-samples in Table 1. The order from top-left to bottom-right corresponds to that in the table. A ratio smaller than 1 at horizon p indicates that Garch(1,1) volatility forecast for the next interval of p days is poorer than that based on the simple BM approach.

at most ten days ahead). We remark that on the last series, corresponding to the index Dow

Jones Industrial (DJI), the GARCH(1,1) model, while not exhibit an IGARCH effect as strong as that of FAZ or NIKKEI, produces extremely big errors in forecasting at almost all horizons.

The over-all behaviour of the two forecasters reported in this section will be confirmed by the following exercise.

3.2. **Trading derivatives.** We will now evaluate the consequences of the IGARCH effect on trading derivatives by observing two traders, G and H, who take opposite positions on the same contract. To emphasize the effects of volatility estimation we assume that both traders dynamically hedge their respective positions. Trader G uses a volatility forecaster based on the Garch model calibrated on the previous 1000 returns, trader H adopts a forecaster based on the sample variance computed on the previous 250 returns. Each trader prices and hedges a given contingent claim according to his volatility forecaster. Trader H uses the volatility forecast given by (3.3), while trader G uses the conditional forecast as defined in (3.2) and also adopted by Engle et al. (1997). The contingent claim considered for the exercise is an at-the-money straddle (i.e. a portfolio of an at-the-money call and an at-the-money put). The payoff of such a contract depends on the movements of the underlying in any directions (positive or negative) hence it is more sensible to volatility than a call or a put alone.

We fix a period of observation of 2000 days. The first 1000 days are necessary to estimate the first set of Garch parameters. After it, a new contract is initiated every week (i.e. every five days). When a contract is initiated at time t_0, the two traders simultaneously state their respective prices V_0^H and V_0^G. Such prices are based on the Black-Scholes model therefore any difference is only due to the different volatility estimates. The deal is struck at time t_0 for a price P_0 that is the average of the two bids V_0^H and V_0^G. The trader who made the highest bid takes the long side (i.e. he buys the contract), the second one takes the short side. Note that both traders believe that the price P_0 is either low or high enough to make a profit. To secure the expected profit, each trader implements a hedging strategy, still based on the Black-Scholes model but depending on his own volatility forecast, until maturity of the contract.

At each time t from the inception of the contract at t_0 until maturity, the hedging portfolio of trader $*$ (G or H) consists of $\xi_t^* = \Delta((\overline{\sigma}_t^*))$ units of the underlying, that is the Black-Scholes Delta computed with the volatility estimated by model $*$, and of η_t^* currency units in the bank account (we assume a zero interest rate). The value of the hedging portfolio at time t is $V_t^* = BS(\overline{\sigma}_t^*)$, that is the Black-Scholes price at time t of the straddle. The initial cost of the hedging strategy is $C_0^* = V_0^*$ and the total cost accumulated up to time t is

$$C_t^* = V_t^* - \sum_{k=0}^{t-1} \xi_k^* (S_{k+1} - S_k),$$

that is the value of the hedging portfolio minus the total trading gains. By opportunely choosing η_T^*, the final value of the replicating portfolio is set to be equal to the straddle's payoff $\|S_T - K\|$. A strategy is "self-financing" when the cost process C_t^* is a constant. The strategies adopted by the two traders do not have to be "self-financing" (and, in general, are not). The final profit-loss of the short position is given by the initial price of the straddle P_0 minus the total final cost of the strategy. For a long position it is given by the total final cost of the hedging strategy minus P_0.

For each of the twelve indexes, and for each trader, we compute a series of profit-losses as follows. Let $r_t, t = 1, \ldots, 2000$, be the log-returns in the sub-sample for a given index. A new contract is initiated at every week, at times t_k, (where $t_0 = 1000$ and $t_{k+1} - t_k = 5$). The hedging portfolios are adjusted every day until maturity. Let t be a time between the inception of the contract and one day before its maturity, then the number of shares of the underlying in the hedging portfolio is given by the Black-Scholes hedge ratio formula for a straddle with strike K and time to maturity τ, that is

$$\xi_t^* = 2\Phi\left(\frac{\log S_t/K + \overline{\sigma}_{t,\tau}^{2,*}/2}{\overline{\sigma}_{t,\tau}^*}\right) - 1,$$

where $\Phi(\cdot)$ is the standard normal cumulative density function, S_t is the price of the underlying at time t, $\sigma_{t,\tau}^*$ is the volatility forecasted at time t by model $*$ for the period from t to $t+\tau$. The value S_t is obtained from the historical time series of log-returns by setting $S_{t_k} = 1$, for each starting time t_k. Since we want the contract to be at-the-money, the strike of the straddle is also set equal to 1.

The goal of the exercise is to check whether there are significant differences in the profit-loss distributions between the two traders.

For maturities shorter than $T = 120$ days, the two performances are close to each other. This should come as expected, since the performances depend on volatility forecasters that tend to be closer for shorter time horizons. However, significant differences do arise for longer maturities. The results for the case $T = 240$ are displayed in Figure 3.2 where the fitted normal distribution to each of the profit-loss series are shown. The normal approximation fits the data reasonably well and provides a clear representation of the results. Each plot reports the normal approximation of the profit-losses of trader G (continuous line) and of trader H (broken line) for the corresponding financial index. The difference is rather small, sometimes almost negligible, for the first eight series. In fact, for these cases there is not a clear winner. The situation changes dramatically for the remaining series (from 9 to 12), notably those affected by a stronger IGARCH effect[4]. In fact, for the last series, the profit-loss of the G trader is negative on average, while that of the

[4]Note that the differences between the traders are the strongest on the DJI series, on which the GARCH(1,1) model, as already observed, produces particularly poor volatility forecasts (see Figure 3.1).

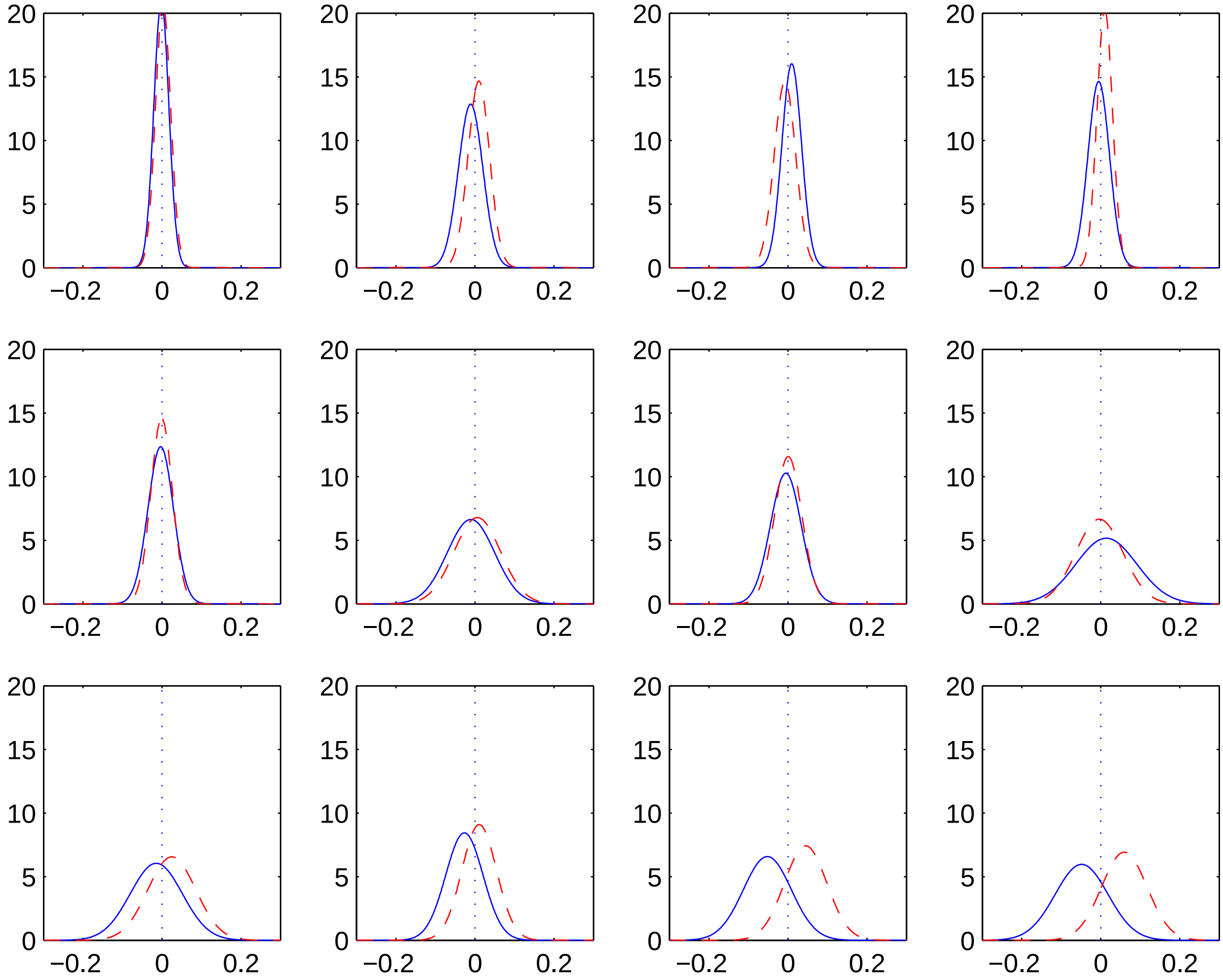

Figure 3.2. *Normal approximations of the profit-loss distributions of the trading strategies on the twelve indexes for the G trader (continuous line) and the H trader (broken line). The contract considered is an at-the-money straddle with maturity* 240 *days. It is evident that the H trader outperforms the G trader on the last four series, affected by a stronger IGARCH effect.*

H trader is positive. The respective variances are comparable, showing that the H trader can be rather confident to gain, as the G trader should be to loose.

4. Conclusions

We performed an empirical analysis of the IGARCH effect, investigating the consequences it can have on trading and hedging of derivative securities. By examining the time series of twelve indexes from major financial markets, we provided empirical evidence that the IGARCH effect is often present. We empirically showed that the IGARCH effect has important consequences on forecasting volatility on longer horizons. We found evidence that the IGARCH effect has a significant impact on a trading system based on the GARCH(1,1) model especially when dealing with contracts of longer maturities.

Overall the present analysis constitutes a contribution to the empirical study of the Garch modeling framework as well as a caveat to some of the problems that may arise when employing it under particular market conditions.

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