On the predictive power of implied volatility indexes: A comparative analysis with GARCH forecasted volatility

Bentes, Sonia R and Menezes, Rui

24 October 2012

On the predictive power of implied volatility indexes: A comparative analysis with GARCH forecasted volatility

Sonia R. Bentes[1*] and Rui Menezes[2]

[1]ISCAL, Av. Miguel Bombarda, 20, 1069-035, Lisbon, Portugal
[2]ISCTE, Av. das Forças Armadas, 1649-025, Lisbon, Portugal

Abstract

This paper examines the behavior of several implied volatility indexes in order to compare them with the volatility forecasts obtained from estimating a GARCH model. Though volatility has always been a prevailing subject of research it has become particularly relevant given the increasingly complexity and uncertainty of stock markets in these days. An important measure to assess the market expectations of the future volatility of the underlying asset is the implied volatility (*IV*) indexes. Generally, these indexes are calculated based on the prices of out-of-the money put and call options on the underlying asset. Sometimes called the "investor fear gauge", the *IV* indexes are a measure of the implied volatility of the underlying index. This study focuses on the implied and GARCH forecasted volatility of some emerging countries and some developed countries. More specifically, it compares the predictive power of the *IV* indexes with the ones provided by standard volatility models such as the ARCH/GARCH (Autoregressive Conditional Heteroskedasticity Model/ Generalized Autoregressive Conditional Heteroskedasticity Model) type models. Finally, a debate of the results is also provided.

Keywords: implied volatility; volatility forecasts, GARCH models, volatility indices

* Corresponding author.
E-mail address: smbentes@iscal.ipl.pt

Introduction

Volatility has always been central to financial theory. A number of reasons have been advanced for that. While Martens and van Dick (2007) considers that assessing financial volatility is important for portfolio management, risk management and option pricing, Daly (2008) identifies, in a more extensive way, six reasons for this interest: (i) first, sharp asset prices fluctuations may lead to an erosion of confidence in the stock markets and reduced flow of capital into this equity markets; (ii) secondly, it is an important factor to determine the probability of bankruptcy of individual firms; (iii) thirdly, it is crucial to determine the bid-ask spread and the market liquidity; (iv) hedging techniques are affected by the volatility level since the price of insurance increases with volatility; (v) high volatility may reduce the level of participation in the economic activity with negative consequences to the investment; and, (vi) Finally, increased volatility may induce regulatory agencies to force firms to allocate a larger percentage of capital to cash equivalent investment to the potential detriment of efficiency in allocations. For a more comprehensive debate on the subject see also Bollerslev *et al.* (1992), Figlewski (1997) and Poon and Granger (2003).

Given the increasing turbulence and instability of stock markets, volatility has become a very active field of research. An important issue in this debate is how well implied volatility (*IV*) predicts future realized volatility (*RV*). The former is based on the theory of options by solving the BS model in order to determine the (corresponding) implied volatility, denoted by σ. Sometimes called the "the investor fear gauge" (Whaley, 2000), IV is widely regarded as the options market's forecast of future volatility. Thus, if option markets are efficient, market implied volatility should be an efficient forecast of future returns volatility. In other words, *IV* should include the information contained in all the variables in the market information set (Christensen and Prabhala, 1998). Thought several studies have addressed this subject no definite answer has come out as empirical results have been mixed so far. In the light of this, the purpose of our paper is to examine the predictive power of *IV*, compare it to the volatility derived from a GARCH-type model and check which one is more suitable to predict *ex-post* volatility.

Besides the need for a re-assessment of the predictive power of *IV* our research is motivated by another shortcoming in the literature: generally, studies on this topic are mainly devoted to developed economies, with only very few focusing only on emerging countries. In fact, there is a variety of studies concerning the *IV* of futures, individual assets, stock market indexes, oil and some other commodities traded in developed economies such as US and EU (Blair, 2001, Becker, 2006, Chen, 2007, Szakmary *et al.* 2003, *inter alia*) but very little regarding implied volatility in emerging markets (*e.g.*, Nam *et al.*, 2006; Vrugt, 2009). This may be due to the fact that only recently *IV*s started to be available in some of these countries (see, for example, India, Korea).

Early papers (*e.g.* Latane and Rendleman, 1976, Chiras and Manaster, 1978 and Beckers, 1981) found that implied volatilities are better estimates of future volatility than the traditional standard deviation. In a subsequent research, Jorion (1995) documents that *IV* is an efficient, though biased, predictor of future volatility for foreign currency futures. In the same line, Fleming *et al.* (1995) for future markets indexes, Christensen and Prabhala (1998) for SP 100 index options and Giot (2003) came to similar results. Subsequently, Szakmary *et al.* (2003) using data from 35 future option markets concluded that for a large majority of the commodities studied the implieds outperform the historical volatility as a predictor of *RV*. Further, GARCH forecasts are not superior to *IV*s. A slightly different conclusion arise Agnolucci (2009) who studied the predictive power of *IV* and GARCH models. According to this author while *IV* does not perform better than GARCH models, there is some information contained in *IV* forecasts that is not contained in those obtained from the GARCH-type models.

In contrast with this stream of research where *IV* dominates, Day and Lewis (1992), and Lamoureux and Lastrapes (1993), for SP 100 and options on ten stocks, respectively, found that implied volatility is biased and inefficient since past volatilities contains predictive information about future volatility beyond that provided by implieds. This is in consonance with Kumar and Shastri (1990), Randolph *et al.* (1990) and Canina and Fliglewsi (1993) who generally concluded that *IV* has little power to predict *RV*. More specifically, the latter found that there is no relation at all between implied and realized volatility. According to Christensen and

Prabhala (1998), Canina and Figlewski (1993) findings may be due to a shorter time horizon used in their study, which exactly precedes the October 1987 crash, where a regime shift occurred. Therefore, implied volatility is expected to be more biased before the crash than afterwards. Apart from this cause, some other reasons may explain this kind of results (Agnolucci, 2009): (i) sample selection bias, given the difficulty in observing *IV* during periods of high turbulence where stock market liquidity becomes a problem to investors (Engle and Rosenberg, 2000); (ii) sample bias, which occurs when *IV* takes into account the presence of low probability events which are not too common in the sample. (iii) bid-ask spreads and, finally, (iv) the use of BS model to get the *IV* of American options. On the other end, critics of *IV* argue consider the latter is not a good predictor of future realized volatility since market prices are determined by several other factors, which are not included in the BS formula, such as, market liquidity and the BS assumption of unlimited arbitrage.

Given this controversy further researches seem to be needed. This is specially so as very few studies address the *IV* predictive power of emerging economies. In sum, our paper makes at least three contributions to literature: (i) it updates early researches on *IV*; (ii) it focuses on emerging economies and (iii) it applies an alternative approach, based on ADL and ECM, to assess the information content of implieds in explaining realized volatility, which to the best of out knowledge has not yet been done so far. More specifically, the latter model adds by clearly separating the short and long run effects in explaining the relation between implied and realized volatility.

The remainder of the paper is organized as follows: Section 2 describes the methodological background. Section 3 presents the empirical results and, finally, in Section 4 we draw the conclusions.

2. Metodological background

In this section we discuss the theoretical framework that motivates the empirical analysis. According to the conventional approach the information content of implied volatility is typically assessed by an OLS regression of the form:

$$RV_t = \alpha_0 + \alpha_i IV_t + u_t, \quad (1)$$

where RV_t denotes the realized volatility for the period t and IV_t represents the implied volatility at the beginning of period t. From expression (1) three hypotheses can be tested. First (H_1) if IV contains at least some information about future realized volatility, coefficient α_i should be nonzero. Second (H_2) if IV is an unbiased estimate of realized volatility then $\alpha_0 = 0$ and $\alpha_i = 1$. Finally (H_3) if implied volatility is efficient, the residuals u_t should be white noise, non-auto correlated, and uncorrelated with any other variable.

Subsequently, to compare the efficiency of implied volatility to that of past realized volatility a multiple regression of the form is estimated:

$$RV_t = \alpha_0 + \alpha_i IV_t + \alpha_h RV_{t-1} + u_t . \qquad (2)$$

Thus (H_4) if $\alpha_i IV_t$ is an efficient forecast, α_h should be not statistically significant and the values of the R^2 and the information criteria of Eq. (2) should be not significantly different from those of Eq. (1).

Though some literature exists which applies this methodology very few studies cover the emerging countries. Additionally, we contribute to the existing literature by introducing an Autoregressive Distributed Lag – ADL(p,q) Model and an Error Correction Model – ECM to study the above-mentioned relationships, which to the best of our knowledge has not been done so far.

An ADL (p,q) model is of the form

$$RV_t = \alpha_0 + \sum_{k=0}^{q} \alpha_{ik} IV_{t-k} + \sum_{j=1}^{p} \alpha_{hj} RV_{t-j} + \varepsilon_t , \qquad (3)$$

and is used to assess dynamical relations between the variables. This is useful for our purposes since it encompasses not only the contemporaneous relations, where a change in one or more explanatory variables causes instant changes in the dependent variable, but also lagged relations between the variables.

In order to improve our analysis an ECM is used, which is expressed as

$$\Delta\left(\ln RV_t\right) = \sum_{k=0}^{p} \alpha_{k1} \Delta\left(\ln IV_{t-k}\right) + \alpha_{ih}\left(RV_{t-p} - \alpha_0 - \alpha_i IV_{t-p}\right) + \varepsilon_t, \tag{4}$$

where $\left(RV_{t-p} - \alpha_0 - \alpha_i IV_{t-p}\right)$ denotes the error correction term and α_{ih} measures the adjustment speed, that is, how RV changes in response to disequilibrium. In the context of univariate modeling taking the first differences to get stationarity seems to be acceptable. However, when the relationship between variables is relevant such a procedure is inappropriate. This is especially so because first difference models only capture short run relations, neglecting the long-run effects. To overcome this problem a solution is to estimate an ECM where both relations are accounted for. Also denominated Equilibrium Correction Model it is interpreted as follows: RV changes between t and $t-1$ as a result of 1) changes in the explanatory variable IV between t and $t-1$ and 2) to correct for any disequilibrium during the previous period.

Alternatively, a GARCH framework can be used to compute the estimated volatility and compare the results with IVs. This is in line with the work of Engle (1992) who considers that financial market volatility may be predictable. Bearing on this he derived the ARCH(q) model. Consider the time series RV_t and the associated prediction error $\varepsilon_t \equiv RV_t - E_{t-1}RV_t$ where E_{t-1} is the expectations operator conditioned on time $t-1$ information. By definition, ε_t is serially uncorrelated with mean zero but the conditional variance of the process σ_t^2 is changing over time. In the classic ARCH(q) process proposed by Engle (1982) σ_t^2 is postulated to be a linear function of the lagged squared innovations implying Markovian dependence dating back only q periods; that is, ε_{t-i}^2 for $i = 1, 2, ..., q$. That is:

$$\sigma_t^2 = \omega + \alpha\left(L\right)\varepsilon_t^2 \tag{5}$$

A Generalized Autoregressive Conditional Heteroskedasticity (GARCH) was then defined by Bollerslev (1986) so that $\varepsilon_t = z_t \sigma_t$, z_t is i.i.d., with zero mean and unit variance

$$\sigma_t^2 = \omega + \alpha\left(L\right)\varepsilon_t^2 + \beta\left(L\right)\sigma_t^2, \tag{6}$$

where $\omega > 0$, $\alpha(L)$ and $\beta(L)$ are polynomials in the lag operator $L\left(L^i x_t = x_{t-i}\right)$ of order q and p, respectively. For stability and covariance stationarity of the ε_t process, all the roots of $\left[1-\alpha(L)-\beta(L)\right]$ and $\left[1-\beta(L)\right]$ are constrained to lie outside the unit circle.

3. Empirical results

3.1 Data and sampling procedure

To conduct our analysis we gathered data from several different countries, such as: BRIC (Brazil, Russia, India and China), some Australasian economies (Korea, Hong-Kong and Australia) and the US, which are used as a benchmark. The choice of these particular spot indexes had to do with the availability of data of the corresponding implied volatility indexes, which are not published for all the emerging countries in the world. This has limited our study to the above-mentioned markets. Thus, the spot indexes used are: BOVESPA (Brazil), RTS Standard Index (Russia), S&P CNX NIFTY (India), CSI 300 (China), KOSPI (Korea), Hang-Seng (Hong-Kong), S&P/ASX (Australia) and SPX (US). The correspondingly IVs indexes comprise: VBOV (Brasil), RTSVX (Russia), INVIXN (India), IVCSI (China), KIX (Korea), VHSI (Hong-Kong), AVIX (Australia) and VIX (US), respectively.

Since *IV*s of each market are not available for the same period and in order not to waste any information contained in the data, which may be crucial to understand the volatility phenomenon, different time lengths were considered for each *IV*. The reason for this lies in the fact that *IV*s started to be traded in very different moments in time according to each Board of Exchange. This is not critical as the aim of our study is to compare the predictive power of *IV* with *RV* and GARCH forecasts within each country and not amongst countries. Therefore, our empirical analysis is based on the following time spans: Brazil – Oct 2003 to July 2012; Russia – Feb 2006 to July 2012; India – Dec 2007 to July 2012; China – Feb 2005 to July 2012; Korea and Hong Kong – Oct 2003 to July 2012; Australia – Feb 2008 to July 2012 and US – Oct 2003 to July 2012. For the same reason, the different calculating methods of *IV*s do not affect our results. Originally, VIX was the first *IV* index to be constructed based on the BS formula. In brief, it represents the expected volatility of the underlying index (SP 100) over the next 30 days. It was calculated by inverting the BS formula in order to determine σ_t. In September 2003 the method of calculation of VIX changed. There are mainly two differences between the old and the new VIX: (i) first, it is based on the SP 500, which is considered a benchmark for the US market; and, (ii) second it is model free, which constitutes its major advantage over the former. Notwithstanding these changes, some emerging countries still rely on the old method.

Another issue which arises when analyzing stock market volatility refers to the method of measuring it. This occurs because volatility is a latent variable. As a result a proxy needs to be computed so that comparisons may be performed (Agnolucci, 2009). Following the established practice in literature (*e.g.*, Christensen and Prabhala, 1998) monthly realized volatility is utilized in our study as a proxy:

$$RV = 100 \times \sqrt{\frac{260}{22} \sum_{i=1}^{22} \left[\ln\left(\frac{P_{t+i}}{P_{t+i-1}} \right) \right]^2} . \tag{7}$$

To determine the 30 days realized volatility non-overlapping observations were used. Data was collected from the Bloomberg database.

3.2 Descriptive statistics

The descriptive statistics for the realized, implied and GARCH volatility for each country appear in Tables 1-3.

Table 1

Descriptive statistics of realized volatilities

	Brazil	Russia	India	China	Korea	Hong-Kong	Australia	US
Mean	26.66169	32.34871	25.65043	27.93043	22.04173	22.42545	19.93018	17.15169
Median	24.40421	25.47996	20.52604	23.93731	19.15381	17.99045	18.36917	13.59675
Maximum	110.3256	144.1859	79.00021	60.21619	85.31131	109.4227	59.98454	82.27708
Minimum	13.28732	12.19904	10.05383	11.46747	9.797445	7.141296	8.629115	6.493272
Std. Dev.	13.22811	21.84182	14.08291	11.70870	11.13861	14.45839	9.694242	12.29182
Skewness	3.272464	2.869206	1.778287	0.911113	2.750250	2.848526	2.000438	2.687427
Kurtosis	18.68150	13.05460	6.238763	2.925273	13.80391	14.94017	8.361718	12.00547
Jarque-Bera	1275.293	435.5790	53.99054	12.47286	649.1618	773.0224	100.6988	485.7782
Probability	0.000000	0.000000	0.000000	0.001957	0.000000	0.000000	0.000000	0.000000
Observations	106	78	56	90	106	106	54	106

Table 2

Descriptive statistics of implied volatilities

	Brazil	Russia	India	China	Korea	Hong-Kong	Australia	US
Mean	47.21525	40.78711	29.18929	39.16783	24.62170	25.49745	25.45017	20.89925
Median	51.86696	32.83595	25.90500	44.93935	22.70500	21.46000	24.23500	17.79000
Maximum	72.59250	167.8919	69.32000	68.05720	81.27000	79.95000	54.12580	59.89000
Minimum	16.01067	18.85370	16.56000	7.753600	14.68000	11.72000	14.56530	10.42000
Std. Dev.	16.95852	25.41428	10.64901	20.10892	9.360423	11.75645	8.614555	9.558026
Skewness	-0.262687	3.199907	1.459176	-0.318112	3.011471	1.775554	1.220109	1.744656
Kurtosis	1.641992	15.03222	5.464257	1.616900	15.89406	6.880860	4.224089	6.399371
Jarque-Bera	9.364230	603.6286	34.04180	8.691549	894.5192	122.2155	16.76937	104.8120
Probability	0.009259	0.000000	0.000000	0.012961	0.000000	0.000000	0.000228	0.000000
Observations	106	78	56	90	106	106	54	106

Table 3

Descriptive statistics of the GARCH forecasted volatilities

	Brazil	Russia	India	China	Korea	Hong-Kong	Australia	US
Mean	27.67779	34.47575	26.89113	29.36611	22.91831	23.35544	20.93284	18.19812
Median	25.37598	28.35141	22.30987	26.77700	20.34085	18.37210	18.47410	13.97304
Maximum	88.51497	127.6114	68.38044	52.48427	71.16136	90.39089	54.54131	73.45655
Minimum	18.19723	17.55152	14.09867	16.94178	13.24314	10.66039	9.942275	8.469710
Std. Dev.	10.41382	19.65444	11.75464	9.380003	9.059967	13.06245	9.321294	11.58373
Skewness	3.553401	2.832476	1.608572	0.841926	2.509832	2.358002	1.789676	2.769811
Kurtosis	19.45332	12.44710	5.396719	2.661769	11.48691	10.26403	6.830035	12.08710
Jarque-Bera	1418.714	394.3528	37.55330	11.06158	429.4088	331.2800	61.83209	500.2438
Probability	0.000000	0.000000	0.000000	0.003963	0.000000	0.000000	0.000000	0.000000
Observations	106	78	56	90	106	106	54	106

As we are dealing with different time horizons, the number of observations for each index varies. Thus, while Brazil, Korea, Hong-Kong and the US total 106 observations, Russia adds up to 78, India to 56, China to 90 and Australia to 54.

Starting with the mean average we find that implied volatilities exceed the corresponding realized volatility for all the time series considered. This finds support in Corrado and Miller (2003) and Christensen and Prabhala (1998), where similar results were documented. Furthermore, the mean difference between realized and implied volatility is substantially greater for Brazil, China and Russia whereas Hong Kong, US and Korea present the shortest differences. Regarding the standard deviation, results are somewhat mixed: India, Korea, Hong-Kong, Australia and US implied volatility show lower dispersion than the realized ones. The opposite holds for the remainder countries. When we take into consideration the GARCH estimates a similar pattern to the realized volatility arises for the mean and standard deviation.

In addition, all the three proxies considered generally show positive skewness (exception made for VBOV and IVCSI) and excess kurtosis. This statistic is only lower than 3 for China realized and implied volatilities and the GARCH volatility estimates and for Brazil implied volatility, which may suggest that these countries might have distinct volatility behaviour when compared to the remainder ones. As expected all volatility series show significant departures from normality as indicated by the Jarque Bera test and may exhibit fat tails since most of them are leptokurtic.

Figures A1-A8 (Appendix A) provide a graphical analysis of the implied, realized and GARCH volatilities for each country. Apart from Brazil and China, whose descriptive statistics have already denoted a distinct behaviour, some common patterns seem to arise: (i) volatility series appear to be synchronized since realized volatility in month m is aligned with implied in the last trading day of month $m-1$. The same occurs with GARCH volatilities. Differences that might occur in this pattern may be due to forecasting errors. (ii) Generally, a consistent behaviour is found for all the proxies considered. (iii) Moreover, RV and GARCH volatilities are closer to each other than the IVs, which might suggest that GARCH volatility is apparently a better predictor of the realized ones than the IV. (iv) Implied volatilities do not anticipate RVs when volatility peaks occur.

3.3 Results

3.3.1 Implied Volatility

Table 4 presents the estimates of α_0 and α_i (Eq. 1) for the four emergent markets (Brazil, Russia, India and China), and for Korea, Hong-Kong, Australia and US.

Table 4

OLS Implied volatility estimates (Eq. 1)

Country	α_0		α_i		$\chi^2(1)$		DW	Adjusted-R^2
Brazil	30.14806	**	-0.07384		-		0.74066	-0.00057
	(3.8180)		(0.0761)					
Russia	8.63855	*	0.58132	**	33.2488	**	1.18215	0.45037
	(3.4832)		(0.0726)					
India	-0.34044		0.89043	**	0.67817		2.01243	0.44322
	(4.1299)		(0.1331)					
China	27.29916	**	0.01612		-		0.62792	-0.01059
	(2.7286)		(0.0620)					
Korea	2.38284		0.79844	**	5.42726	*	1.46384	0.44492
	(2.2777)		(0.0865)					
Hong-Kong	-2.30788		0.97003	**	0.16343		1.88884	0.61850
	(2.0797)		(0.0741)					
Australia	-1.69015		0.84952	**	2.16187		1.28966	0.56161
	(2.7473)		(0.1023)					
US	-3.10419		0.96922	**	0.13795		1.19722	0.56384
	(1.9032)		(0.0829)					

Standard error estimates are in brackets
** Statistically significant at the 1% level
* Statistically significant at the 5% level

The results above show that, for the BRIC countries, the constant term α_0 is non-significantly different from zero except for India. For the same subset, the slope coefficient α_i only appears significantly in the regressions for Russia (0.58132) and India (0.89043). A $\chi^2(1)$ test for the null hypothesis that $\alpha_i = 1$ was also performed and the null was not only rejected for India. Thus, for the BRIC countries, H_1 (*IV* contains at least some information about future *RV*) is only statistically confirmed for Russia and India. On the other hand, H_2 (*IV* is an unbiased estimate of the future *RV*), is only statistically confirmed for India. Contrarily, in the cases of Brazil and China *IV* does not appear to contain any information that can be useful to predict future *RV*, at least in the long-run equilibrium relationship.

Turning now to the estimates of α_0 and α_i (Eq. 1) for Korea, Hong-Kong, Australia and the US, Table 4 show that the null hypothesis of $\alpha_0 = 0$ is not rejected in every case, whereas $\alpha_i = 0$ is rejected at 1% or lower in all cases. Furthermore, the $\chi^2(1)$ test for the null hypothesis of $\alpha_i = 1$ is only rejected (at the 5% level) for Korea, thus supporting the conclusion that *IV* contains at least some information about future *RV* (H_1) in all these cases, and that *IV* is an unbiased estimate of the future *RV* (H_2) in Hong-Kong (α_i=0.97003), Australia (α_i=0.84952) and the US (α_i=0.969).

Finally, regarding H_3 (*IV* is efficient if the residuals u_t are white noise, non-auto correlated and uncorrelated with any other variable). Table 5 presents the residual's diagnostics of autocorrelation [Breusch-Godfrey serial correlation LM test - $\chi^2(2)$] and Pearson correlation with the explanatory variable for each regression. ADF tests on the residuals rejected the null of a unit root in all cases. Likewise, tests for residual's normality also rejected the null for all countries. Therefore, apart from stationarity and the evidence of no correlation of the residuals with other variables, H_3 is not (globally) confirmed in any of the estimated regressions.

Table 5

OLS Implied volatility residual's diagnostics (Eq. 1)

Country	$\chi^2(2)$	p-value		ρ-coeff	t-stats	ADF		J-B	
Brazil	42.38127	0.0000	**	-4.61E-15	-4.70E-14	-4.86770	**	1351.065	**
Russia	20.44255	0.0000	**	-7.61E-16	-6.63E-15	-6.29018	**	426.9766	**
India	0.639823	0.7262		6.40E-16	4.70E-15	-7.39663	**	164.9593	**
China	44.94833	0.0000	**	-1.87E-15	-1.75E-14	-3.99191	**	12.76808	**
Korea	11.37679	0.0034	**	-4.23E-15	-4.32E-14	-7.74477	**	1360.393	**
Hong-Kong	0.745844	0.6887		-2.91E-16	-2.97E-15	-9.64625	**	2050.436	**
Australia	8.021146	0.0181	*	5.12E-16	3.69E-15	-5.04392	**	43.24141	**
US	20.24572	.00000	**	4.41E-15	4.50E-14	-6.75050	**	1036.340	**

** Statistically significant at the 1% level
* Statistically significant at the 5% level

Table 6 exhibits the estimates of α_0, α_i and α_h (Eq. 2) for the countries considered in this study.

Table 6

AR(1) Implied volatility estimates (Eq. 2)

Country	α_0		α_i		α_h		$\chi^2(1)$		DW	Adjusted-R^2
Brazil	9.14554	*	0.01205		0.63678	**	10.64169	**	1.93741	0.39050
	(4.0126)		(0.0617)		(0.0778)					
Russia	9.00710	**	-0.31209		1.11221	**	7.1992	**	1.69663	0.59935
	(3.0113)		(0.1779)		(0.2071)					
India	-1.45660		1.04433	**	-0.12938		0.35688		1.73402	0.43567
	(4.6852)		(0.3139)		(0.2388)					
China	8.15143	**	0.01348		0.68743	**	10.63752	**	2.33100	0.45566
	(3.0223)		(0.0464)		(0.0791)					
Korea	4.23053		0.37352		0.39039	*	7.39487	**	1.69940	0.46474
	(2.3988)		(0.2111)		(0.1773)					
Hong-Kong	-4.00381		1.24294	**	-0.23490		0.01012		1.70347	0.62081
	(2.4693)		(0.2263)		(0.1840)					
Australia	-1.50344		0.75836	**	0.10998		1.53677		1.36423	0.55693
	(3.0021)		(0.2212)		(0.1921)					
US	0.28674		0.43064	*	0.46181	**	1.65749		1.65001	0.60052
	(2.1233)		(0.1918)		(0.1492)					

Standard error estimates are in brackets
** Statistically significant at the 1% level
* Statistically significant at the 5% level

The hypothesis to be tested in this regression consists in comparing the efficiency of the *IV* to that of the past *RV*, with the null $\alpha_h = 0$. This only holds for India, Hong-Kong and Australia. For these countries we also found out that the R^2 coefficients are not significantly different between both regressions (India: 0.44322 *vs.* 0.43567; Hong-Kong: 0.61850 *vs.* 0.62081; Australia: 0.56161 *vs.* 0.55693). Similarly, Schwarz Information Criterion provided the same conclusions (India: 7.64961 *vs.* 7.73650; Hong-Kong: 7.28572 *vs.* 7.32426; Australia: 6.66631 *vs.* 6.74229). A $\chi^2(1)$ test for the null hypothesis that $\alpha_i + \alpha_h = 1$ was performed and the null was not rejected for India, Hong-Kong and Australia.

Although the residuals of the estimated regressions are stationary for all countries (ADF tests were performed and the null hypothesis of a unit root was rejected at the 1% level or lower, in all cases), it is worthy to note that the residual's serial correlation may distort our conclusion about the capability of *IV* to predict the future

RV in Eq. (1) and additionally, to some extent, in Eq. (2). This is evidenced by the low DW statistics obtained in all cases except for India (2.01243) in Eq. (1) and, to some extent, for Hong-Kong (1.88884). Nevertheless, the AR(1) results obtained from estimating Eq. (2), for these two countries, did not improve the DW statistic, on the contrary they turned out to be worse. In the attempt to avoid this problem we estimated eight ADL(p,q) models for the same financial markets analyzed before. This was conducted by estimating Eq. (3), where the number of lags on *RV* (p) and *IV* (q) were chosen in order to eliminate the residual's autocorrelation. For our purpose, $p = q \leq 2$ was enough to eliminate the autocorrelation (the number of lags used in each case differ from country to country). A summary of the results is presented in Table 7.

Table 7

ADL(p,q) [$p \leq 2$ and $q \leq 2$] Implied volatility estimates (Eq. 3)

Country	α_0		$\alpha_{i0}+\alpha_{i1}+\alpha_{i2}$	$\chi^2(1)$ - $\sum=0$		$\chi^2(1)$ - $\sum=1$		DW	Adjusted-R^2
Brazil	9.14554 (4.0126)	*	0.01205	0.03816		-		1.93741	0.39050
Russia	7.75569 (3.2211)	*	-0.18140	4.89672	*	207.705	**	1.89863	0.63435
India	-0.34044 (4.1299)		0.89043	44.7825	**	0.67817		2.01243	0.44322
China	6.37977 (3.1241)	*	0.00442	0.00929		-		1.99626	0.48247
Korea	4.46194 (2.3415)		0.71499	63.8171	**	10.1402	**	1.80989	0.47856
Hong-Kong	-3.25178 (2.4549)		1.25790	31.9077	**	1.34127		2.02420	0.63316
Australia	-3.45396 (2.5808)		0.94325	93.1427	**	0.33719		2.00393	0.73198
US	1.26253 (2.0231)		0.45601	6.32674	*	9.00378	**	1.91623	0.64367

Standard error estimates are in brackets
** Statistically significant at the 1% level
* Statistically significant at the 5% level

To verify H_1 in this model, we should test whether $\alpha_{i0}+\cdots+\alpha_{iq}\neq 0$. A $\chi^2(1)$ test for the null hypothesis of $\alpha_{i0}+\cdots+\alpha_{iq}=0$ (q = 0, …, 2) was performed. The null was not only rejected for Brazil and China. To verify H_2, $\alpha_0 = 0$ and $\alpha_{i0}+\cdots+\alpha_{iq}=1$ (q = 0, …, 2) were considered. In this case, the joint null was not rejected for India, Hong-

Kong and Australia however the null $\alpha_{i0} + \cdots + \alpha_{iq} = 1$ was rejected at less than 1% for the US.

Finally, H_3 can be verified by looking at the properties of the residuals u_t (Table 8). Serial correlation, correlation with the explanatory variable and stationarity are no longer a problem. However, normality is not only rejected for Australia. Despite this limited evidence, we believe that ADL regressions provide a better framework for the type of analysis under consideration than static OLS regressions.

Table 8

ADL(p,q) [$p \leq 2$ and $q \leq 2$] Implied volatility residual's diagnostics (Eq. 3)

Country	$\chi^2(2)$	p-value	ρ-coeff	t-stats	ADF		J-B	
Brazil	0.87503	0.6456	2.93E-15	2.98E-14	-9.84962	**	450.0783	**
Russia	1.17036	0.5570	-0.04515	-0.38885	-8.21263	**	95.76550	**
India	0.63982	0.7262	6.40E-16	4.70E-15	-7.39663	**	164.9593	**
China	1.38352	0.5007	-2.21E-15	-2.05E-14	-9.26492	**	6.830386	*
Korea	3.84155	0.1465	-3.03E-15	-3.08E-14	-9.22668	**	1099.113	**
Hong-Kong	2.95531	0.2282	2.26E-15	2.29E-14	-10.3402	**	1096.995	**
Australia	0.82091	0.6633	9.58E-15	6.70E-14	-8.06105	**	0.516948	
US	3.01102	0.2219	6.33E-15	6.42E-14	-9.73723	**	476.8231	**

** Statistically significant at the 1% level
* Statistically significant at the 5% level

On the basis of the ADL(1,1) model one can obtain the corresponding ECM for the countries with significant α_i in the static OLS regression. This leads us to the exclusion of Brazil and China from this analysis. Table 9 shows the ECM implied volatility estimates α_{01} and α_{ih} for all the other countries. The α_{01} coefficient provides information about the short-run adjustment of *RV* on *IV* while α_{ih} indicates the speed of adjustment to deviations in the long-run relationship between *IV* and *RV*.

Table 9

ECM Implied volatility estimates (Eq. 4)

Country	α_{01}		α_{ih}		DW	Adjusted-R^2
Brazil	-		-		-	-
	-		-			
Russia	0.38489		-0.00777	*	2.20015	0.03913
	(0.2357)		(0.0038)			
India	0.96187	**	-0.02640	**	1.89021	0.26885
	(0.2771)		(0.0058)			
China	-		-		-	-
	-		-			
Korea	1.18974	**	-0.02805	**	2.10301	0.17797
	(0.2547)		(0.0054)			
Hong-Kong	0.79359	**	-0.01988	**	2.22145	0.17797
	(0.1982)		(0.0042)			
Australia	1.04664	**	-0.02974	**	2.25432	0.26761
	(0.2479)		(0.0079)			
US	0.90436	**	-0.02117	**	2.27419	0.13160
	(0.2420)		(0.0057)			

Standard error estimates are in brackets

** Statistically significant at the 1% level

* Statistically significant at the 5% level

As can be seen, there are both significant short- and long-run adjustments in the relationship between *IV* and *RV* for India, Korea, Hong-Kong, Australia and US. For Russia there are only significant long-run adjustments. The short-run coefficients span from 0.79 to 1.19, whereas the speed of adjustment coefficient ranges from 0.01 to 0.03. This means that a deviation from the long-run relationship between *RV* and *IV* takes a very short time to re-attain equilibrium, with the lowest duration occurring for Russia.

3.3.2 GARCH Forecasted Volatility

This subsection focus on the results obtained from regressing the realized volatility (*RV*) on the GARCH forecasted volatility (*GV*). Table 10 presents the estimates of $\alpha_0^{'}$ and $\alpha_i^{'}$ (Eq. 1) for all the countries under consideration. The models used in these computations are those defined in Section 2, Eq. (2-4). To compute these estimates the explanatory variable *IV* was replaced by *GV*. The daily GARCH forecasted volatility was obtained by the model $\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2$, and from these estimates the monthly time series was constructed by

$$GV = 100 \times \sqrt{\frac{260}{22}\sum_{i=1}^{22}\sigma_t^2}\ . \tag{8}$$

Table 10

OLS GARCH volatility estimates (Eq. 1)

Country	α'_0		α'_g		$\chi^2(1)$		DW	Adjusted-R^2
Brazil	-5.39136	**	1.15808	**	9.54133	**	2.02762	0.82957
	(1.5125)		(0.0512)					
Russia	-5.04763	**	1.08471	**	9.34488	**	2.01137	0.95212
	(1.0980)		(0.0277)					
India	-4.62942	**	1.12602	**	5.12057	*	2.77774	0.88117
	(1.6320)		(0.0557)					
China	-3.83714		1.08178	**	1.51704		2.27046	0.74821
	(2.0457)		(0.0664)					
Korea	-4.02714	**	1.13747	**	9.02924	**	2.18473	0.85461
	(1.1267)		(0.0457)					
Hong-Kong	-0.86179		0.99708	**	0.00384		2.27288	0.80965
	(1.2597)		(0.0471)					
Australia	-0.25251		0.96416	**	0.43931		2.13325	0.85676
	(1.2370)		(0.0541)					
US	-1.09609		1.00273	**	0.00643		1.84419	0.89193
	(0.7334)		(0.0340)					

Standard error estimates are in brackets
** Statistically significant at the 1% level
* Statistically significant at the 5% level

It is worthy to note that the constant term estimates α'_0 are significantly different from zero (1%) in the regressions for Brazil, Russia, India and Korea, while the slope coefficient estimates α'_i are significantly non-zero (1%) in all regressions. For the null $\alpha_i^{'} = 1$, the $\chi^2(1)$ test denotes non-rejection for China, Hong-Kong, Australia and the US, and rejection at 5% for India. Thus, H_1 is confirmed in all cases and H_2 is confirmed for China, Hong-Kong, Australia and the US. Although these results do not depart much from those obtained by implied volatility (*IV*), the overall performance of the models is greatly improved, as can be seen by the R^2 coefficients obtained.

Regarding H_3, Table 11 presents the residual's diagnostics as described above. There is evidence that this hypothesis is only confirmed for China. In addition, residual's serial correlation is still present in the regressions for Brazil, Russia, India, Korea and US.

Table 11

OLS GARCH volatility residual's diagnostics (Eq. 1)

Country	$\chi^2(2)$	*p*-value		ρ-coeff	*t*-stats	ADF		J-B	
Brazil	9.35437	0.0093	**	2.16E-14	2.21E-13	-9.60898	**	143.5438	**
Russia	11.0332	0.0040	**	-1.15E-14	-1.00E-13	-8.97638	**	61.17708	**
India	14.3631	0.0008	**	-5.31E-15	-3.90E-14	-5.86286	**	9.894256	**
China	3.46968	0.1764		9.34E-15	8.76E-14	-10.7583	**	3.150820	
Korea	16.7471	0.0002	**	-5.30E-15	-5.41E-14	-10.9854	**	408.3477	**
Hong-Kong	3.85708	0.1454		-9.75E-15	-9.94E-14	-11.8877	**	937.7121	**
Australia	0.78049	0.6769		5.55E-15	4.00E-14	-8.46932	**	16.40415	**
US	7.69442	0.0213	*	4.62E-15	4.72E-14	-8.38982	**	701.6241	**

** Statistically significant at the 1% level
* Statistically significant at the 5% level

Table 12 presents the estimates of $\alpha_0^{'}$, $\alpha_g^{'}$ and $\alpha_h^{'}$ (Eq. 2) for every country. The null hypothesis in H_4 that implies that $\alpha_h^{'} = 0$ is rejected at less than 1% in all regressions, which indicates that *GV* is not completely efficient to forecast current *RV*, and, past *RV* also plays a predictive role in this relationship. In all cases, the R^2 coefficient is significantly higher for Eq. (2) than for Eq. (1). The usual $\chi^2(1)$ test for the null hypothesis of $\alpha_g^{'} + \alpha_h^{'} = 1$ does not only reject the null for Australia and the US. Residuals of the estimated regressions are stationary in all cases (ADF tests were performed and the null hypothesis of a unit root was rejected at the 1% level or lower in all cases). Nevertheless, residual's serial correlation is now more pronounced.

Table 12

AR(1) GARCH volatility estimates (Eq. 2)

Country	α'_0		α'_g		α'_h		$\chi^2(1)$		DW	Adjusted-R^2
Brazil	-7.74294	**	1.80944	**	-0.59168	**	37.77059	**	2.11423	0.92108
	(1.0580)		(0.0691)		(0.0543)					
Russia	-5.48006	**	1.42911	**	-0.35419	**	19.1379	**	3.00801	0.98202
	(0.6804)		(0.0353)		(0.0318)					
India	-4.58851	**	1.60075	**	-0.49523	**	12.73945	**	2.67284	0.96723
	(0.8660)		(0.0498)		(0.0418)					
China	-9.41692	**	2.15356	**	-0.92547	**	18.81861	**	1.69810	0.86083
	(1.6681)		(0.1360)		(0.1094)					
Korea	-6.02685	**	1.86278	**	-0.66516	**	53.39386	**	2.66822	0.95089
	(0.6730)		(0.0577)		(0.0469)					
Hong-Kong	-3.22234	**	2.15548	**	-1.10765	**	4.34837	*	2.17385	0.95607
	(0.6228)		(0.0669)		(0.0603)					
Australia	-0.29538		1.56710	**	-0.61101	**	1.85862		2.88668	0.95299
	(0.7222)		(0.0679)		(0.0638)					
US	-1.48458	**	1.56782	**	-0.57987	**	0.25455		2.22811	0.94769
	(0.5164)		(0.0586)		(0.0551)					

Standard error estimates are in brackets
** Statistically significant at the 1% level
* Statistically significant at the 5% level

In order to sort out the problem of residual's serial correlation, eight ADL(p,q) models were estimated, whose results are depicted in Table 13. This was accomplished by replacing *IV* by *GV* in Eq. (3). In our case, $p \leq 3$ and $q \leq 2$ was enough to eliminate autocorrelation.

Table 13

ADL(p,q) [$p \leq 3$ and $q \leq 2$] GARCH volatility estimates (Eq. 3)

Country	α'_0		$\alpha'_{g0}+\alpha'_{g1}+\alpha'_{g2}$	$\chi^2(1)$ - $\sum=0$		$\chi^2(1)$ - $\sum=1$		DW	Adjusted-R^2
Brazil	-7.74294 (1.0580)	**	1.80944	686.063	**	137.293	**	2.11423	0.92108
Russia	-11.5229 (1.0940)	**	2.69817	189.124	**	74.9155	**	2.06632	0.98879
India	-7.1071 (1.0747)	**	2.10772	96.7281	**	26.7169	**	2.01079	0.97390
China	-10.1483 (1.5142)	**	2.52649	308.007	**	112.438	**	2.14820	0.88909
Korea	-9.5874 (0.9878)	**	2.80174	207.754	**	85.9169	**	2.02757	0.96077
Hong-Kong	-2.2921 (0.6164)	**	1.88005	482.785	**	105.786	**	2.28625	0.96426
Australia	-0.4461 (0.6824)		2.41304	131.199	**	44.9894	**	1.83396	0.96466
US	-1.8259 (0.5970)	**	2.00076	96.1435	**	24.0541	**	1.87717	0.95177

Standard error estimates are in brackets
** Statistically significant at the 1% level
* Statistically significant at the 5% level

In this model, H_1 can be tested by the null $\alpha'_{g0}+\cdots+\alpha'_{gq}=0$ (q = 0, …, 2). The usual $\chi^2(1)$ test indicates that the null is rejected in all cases at less than 1%. Thus we may conclude that GARCH forecasted volatility contains information about future realized volatility for every country. Likewise, to verify H_2 we test whether $\alpha'_0=0$ and $\alpha'_{g0}+\cdots+\alpha'_{gq}=1$ (q = 0, …, 2). The former is only not rejected at standard levels for Australia. The latter is rejected in all cases at 1% or less and, therefore, H_2 is not confirmed for the GARCH volatility regressions. On the other hand, H_3 can be verified by looking at the properties of the residuals u_t (Table 14). Serial correlation, correlation with the explanatory variable and stationarity is no problem. Likewise, normality is also no longer problematic for Russia, India and Australia, but non-normality still characterizes the remaining countries. Once again, we believe that ADL regressions provide a better framework for the type of analysis under consideration than static OLS regressions.

Table 14

ADL(p,q) [$p \leq 3$ and $q \leq 2$] GARCH volatility residual's diagnostics (Eq. 3)

Country	$\chi^2(2)$	p-value	ρ-coeff	t-stats	ADF		J-B	
Brazil	0.82682	0.6614	3.65E-14	3.71E-13	-10.7569	**	35.44590	**
Russia	1.15281	0.5619	-2.74E-14	-2.36E-13	-9.08405	**	1.859056	
India	1.15066	0.5625	2.45E-14	1.77E-13	-7.89035	**	0.104006	
China	2.21118	0.3310	-1.03E-14	-9.52E-14	-10.0058	**	33.74189	**
Korea	3.62617	0.1632	-5.13E-15	-5.18E-14	-10.2485	**	19.48201	**
Hong-Kong	3.56876	0.1679	-2.84E-14	-2.85E-13	-11.6241	**	28.87801	**
Australia	1.93026	0.3809	9.05E-15	6.40E-14	-6.61707	**	4.122975	
US	3.96744	0.1376	1.16E-15	1.17E-14	-9.52131	**	535.8316	**

** Statistically significant at the 1% level
* Statistically significant at the 5% level

Finally, on the basis of the ADL(1,1) model one can obtain the corresponding ECM for the eight countries analyzed in the static OLS regression. For all countries, the ECM GARCH forecasted volatility estimates $\alpha_{01}^{'}$ and $\alpha_{gh}^{'}$ were computed, where the former provides information on the short-run adjustment of *RV* on *GV* and the latter indicates the speed of adjustment to deviations in the long-run relationship between *GV* and *RV*. The results are shown in Table 15.

Table 15

ECM GARCH volatility estimates (Eq. 4)

Country	α'_{01}		α'_{gh}		DW	Adjusted-R^2
Brazil	1.71900 (0.0965)	**	-0.03889 (0.0034)	**	2.64499	0.75896
Russia	1.46472 (0.0633)	**	-0.03374 (0.0035)	**	2.77331	0.87702
India	1.59326 (0.0666)	**	-0.04401 (0.0032)	**	2.69773	0.81420
China	2.28956 (0.1250)	**	-0.05091 (0.0030)	**	2.55984	0.81420
Korea	1.65314 (0.0890)	**	-0.04758 (0.0042)	**	2.85364	0.77048
Hong-Kong	1.58826 (0.1075)	**	-0.03391 (0.0031)	**	2.57388	0.68991
Australia	1.51654 (0.0970)	**	-0.06366 (0.0060)	**	2.50565	0.83180
US	1.45231 (0.0958)	**	-0.05003 (0.0059)	**	2.57758	0.68852

Standard error estimates are in brackets
** Statistically significant at the 1% level
* Statistically significant at the 5% level

All the coefficients are significantly different from zero at less than 1% both for short- and long-run adjustments in the relationship between *GV* and *RV*. The short-run coefficients span 1.45-2.29, whereas the speed of adjustment coefficient spans 0.03-0.06. Although a deviation from the long-run relationship between *RV* and *GV* still takes a very short time to re-attain equilibrium, with the lowest duration occurring for Russia, these coefficients are higher than those obtained for the implied volatility. However, the results for the *GV* models appear to be more consistent across countries than those for the *IV* models.

4. Conclusions

This paper analyzes the ability of implied and GARCH forecasted volatility to predict realized volatility in eight stock markets over the world. These markets include the four BRIC countries, Korea, Hong-Kong, Australia and US. The implied volatility (*IV*) and the GARCH forecasted volatility (*GV*) are used separately as regressors in several model specifications which attempt to capture the behavior of realized volatility from October 2003 until July 2012. In addition to the static Ordinary Least Squares [OLS] and the first order Autoregressive [AR(1)] regressions, we also use Autoregressive Distributed Lag [ADL(*p.q*)] models and Error Correction models [ECM] to capture the dynamic properties of these relations. ADL(*p.q*) models allow us to remove the residual's autocorrelation that is evident in the static OLS regressions. In addition, the ECM enables us to separate the short-run from the long-run dynamics. This is important insofar it allows us to understand whether the "predictors" (implied and GARCH forecasted) are able to "adapt" themselves to the actual evolution of the realized volatility and how fast do they adapt.

The methodological framework used in this paper allows us to infer about four main hypotheses that are important in the relationship between the implied and the realized volatility: 1) implied volatility contains information about future realized volatility; 2) implied volatility is an unbiased estimate of realized volatility 3) implied volatility is efficient; and 4) implied volatility is a more efficient forecast than the past realized volatility. The same hypotheses apply also to the relationship between the GARCH forecasted and the realized volatility.

Generally, our results show that the first hypothesis holds in almost all cases both for the implied volatility and the GARCH forecasted volatility. However, for the implied volatility, the second hypothesis is confirmed only for India, Hong-Kong, Australia and US. For the GARCH forecasted volatility, the second hypothesis is confirmed for China, Hong-Kong, Australia and the US. That is, not surprisingly, *IV* and *GV* are “more reliable” predictors of *RV* in the developed economies than in the emergent economies analyzed in this study, but *IV* also performs well for India and *GV* for China.

The third hypothesis is not confirmed in the OLS neither in the ADL implied volatility regressions. Although the ADL(p,q) specification could remove the residual’s serial correlation in all cases, the third hypothesis is only holds for Australia in the implied volatility model. For the GARCH forecasted volatility, the third hypothesis is bear out in the OLS model for China and in the ADL model for Russia, India and Australia.

Finally, regarding the fourth hypothesis, our results show that implied volatility is more efficient than past realized volatility to forecast current realized volatility in India, Hong-Kong and Australia. For the GARCH forecasted volatility model our results show that both *GV* and past *RV* add information to explain the variation of current *RV* in all the cases. In the overall, however, the GARCH forecasted volatility model performs better than the implied volatility model. When deviations from the long-run equilibrium relationship between realized volatility and implied volatility (or GARCH forecasted volatility) occur, the time to readjust to equilibrium is quite short, that is, there is a fast (almost immediate) reaction of the predictors to changes in the realized volatility.

To summarize, our results are not in accordance with some researches which lead to the conclusion that implied volatility is an unbiased estimate of future realized volatility. We found that GARCH forecasted volatility is a better predictor than implied volatility. Our main contribution to the existing literature is the use of a dynamic modeling framework (ADL and ECM) in order to correct for residual autocorrelation and the dependence of current realized volatility on past realized and current and past implied volatility (GARCH forecasted volatility). To the best of our knowledge this has not yet been done so far in the context of *IV*, *RV* and GARCH forecasted volatility.

References:

Agnolucci, P. (2009). Volatility in crude oil futures: A comparison of the predictive ability of GARCH and implied volatility models, *Energy Economics* 31, 316-321.

Becker, R., Clements, A.E. and White, S.I. (2006). On the informational efficiency of S&P500 implied volatility, *The North American Journal of Economics and Finance* 17, 139-153.

Beckers, S. (1981). Standard deviation implied in options prices as prdictors of future stock price variability, *Journal of Banking and Finance* 5, 363-381.

Blair, J.B., Poon, S.-H. and Taylor, S.J. (2001). Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns, *Journal of Econometrics* 105, 5-26.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* . 31, 307-327.

Bollerslev, T., Chou, R.K. and Kroner, K.F. (1992). ARCH modeling in finance: A review of the theory and empirical evidence, *Journal of Econometrics* 52, 5-59.

Canina, L. and Fliglewsi, S. (1993). The informational content of implied volatility, Review of Financial Studies 6 (3), 659-681.

Chen, E.-T, and Clements, A. (2006). S&P 500 implied volatility and monetary policy announcements, *Finance Research Letters* 4, 227-232.

Chiras, D.P. and Manaster, S., (1978). The information content of option prices and a test of market efficiency, Journal of Financial Economics 6 (2/3), 213-234.

Christensen, B.J. and Prabhala, N.R. (1998). The relation between implied and realized volatility, *Journal of Financial Economics* 50, 125-150.

Daly, K. (2008). Minireview: Financial volatility: Issues and measuring techniques, *Physica A* 387, 2377-2393.

Day, T. and Lewis, C. (1992). Stock market volatility and the information content of stock index options, *Journal of Econometrics* 52, 267-287.

Engle, R.F. and Rosenberg, J. (2000). Testing the volatility term structure using option hedging criteria, *Journal of Derivatives* 8, 10-28.

Figlewski, S. (1997). Forecasting volatility, *Financial Markets Institutions and Instruments* 6, 1-88.

Fleming, J., Ostdiek, B., and Whaley, R.E. (1995). Predicting stock market volatility: a new measure, *Journal of Futures Markets* 15, 265-302.

Giot, P. (2003). The information content of implied volatility in agricultural commodity markets, *The Journal of Future Markets* 23, 441-454.

Kumar, R. and Shastri, K. (1990). The predictive ability of stock prices implied in option premia, *Advances in Futures and Options Research* 4 (1), 165-176.

Lamoureux, C.G. and Lastrapes, W. (1993). Forecasting stock returns variance: towards understanding stochastic implied volatility, *Review of Financial Studies* 6, 293-326.

Latane, H.A. and Rendleman, Jr. J.R., (1976). Standard deviations of stock price ratios implied in option prices, *Journal of Finance* 31 (2), 369-381.

Martens, M. and Dick, D. (2007). Measuring volatility with realized range, *Journal of Econometrics* 1438 (2007), 181-207.

Nam, S.O, Oh, S.Y., Kim, H.K. and Kim, B.C. (2006). An empirical analysis of price discovery and pricing bias in KOSPI 200 stock index derivatives markets, *International Review of Financial Analysis* 15, 398-414.

Poon, S.H. and Granger, C.W.J. (2003). Forecasting volatility in financial markets: A review, *Journal of Economic Literature* 41, 478-488.

Randolph, W.L., Rubin, B.L. and Cross, E.M. (1990). The response of implied standard deviations to changing market conditions, *Advances in Futures and Options Research* 4 (1), 265-280.

Vrught, E.B. (2009). US and Japanese macroeconomic news and stock market volatility in Asia-Pacific, *Pacific-Basin Finance Journal* 17, 611-627.

Whaley, R.E. (2000). The investor fear gauge, *Journal of Portfolio Management* 23, 12-26.

Appendix A

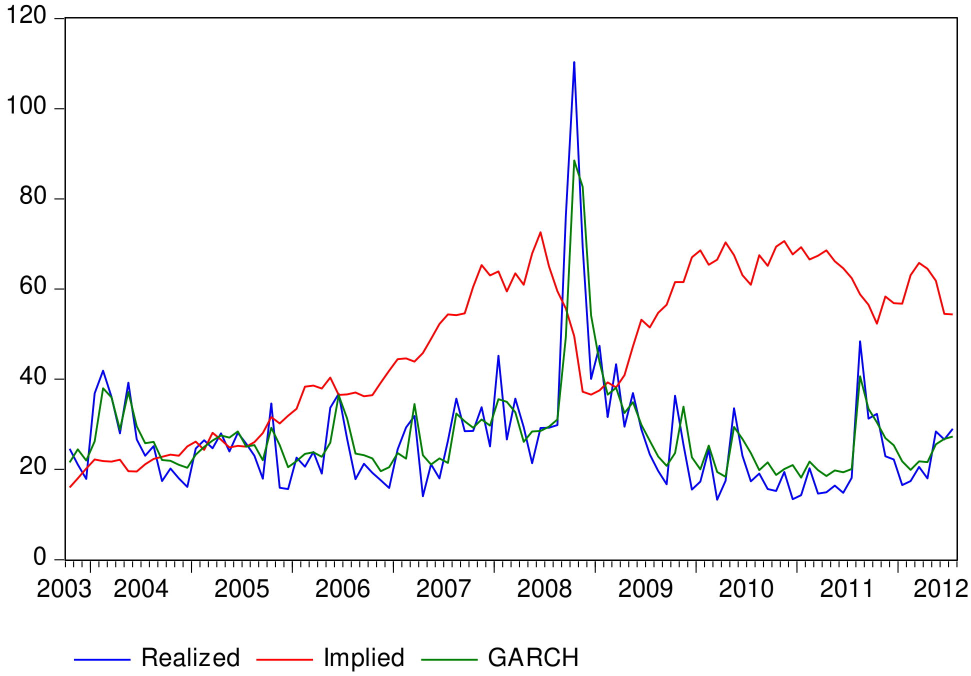

Fig. A1. Realized, Implied and GARCH volatility of Brazil

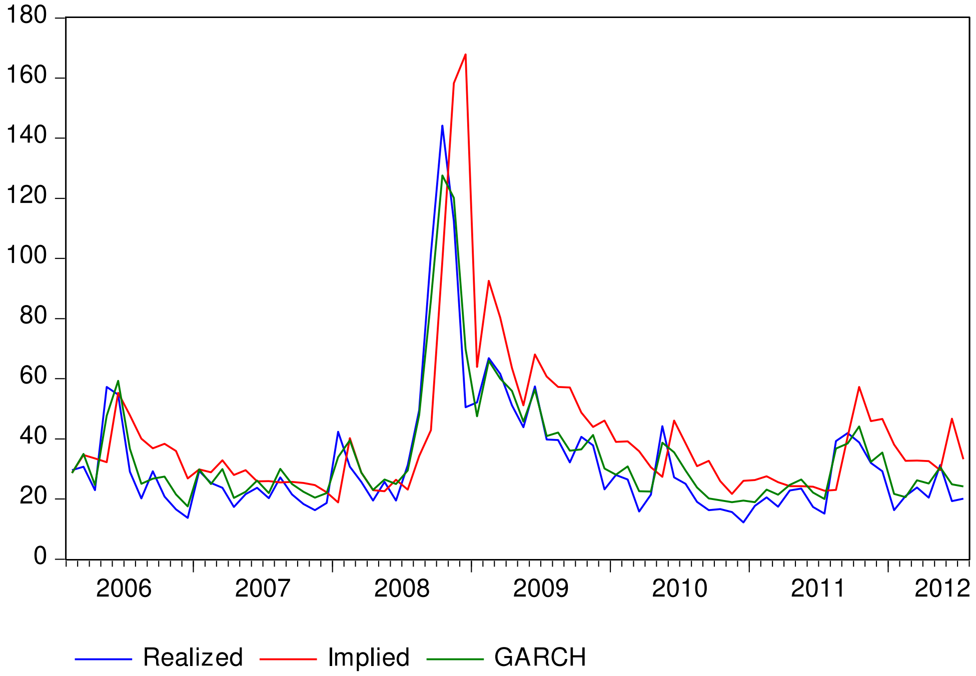

Fig. A2. Realized, Implied and GARCH volatility of Russia

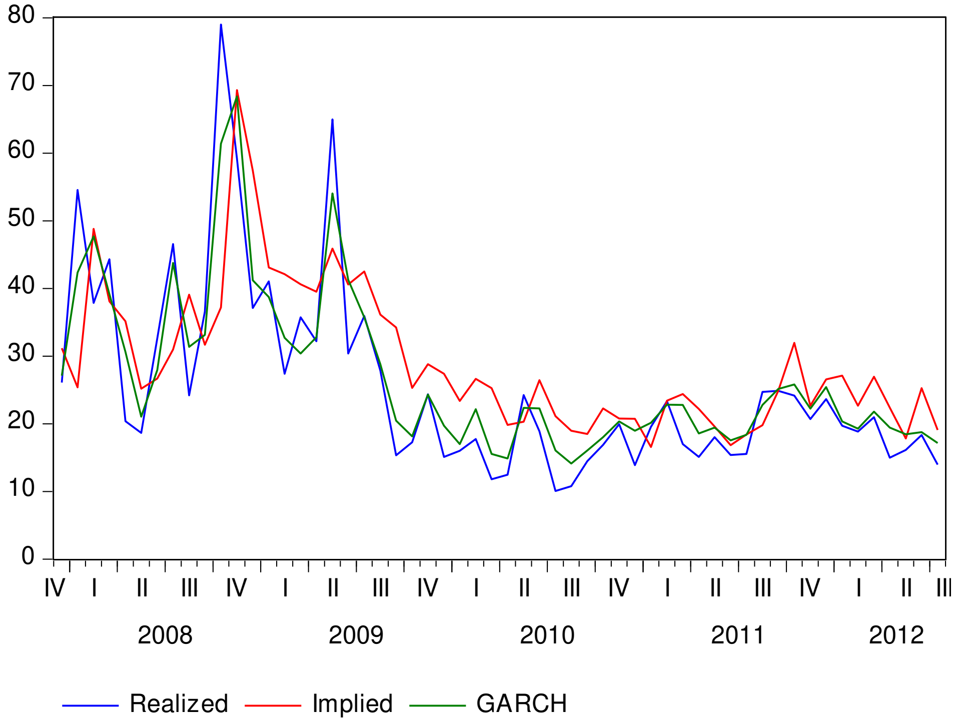

Fig. A3. Realized, Implied and GARCH volatility of India

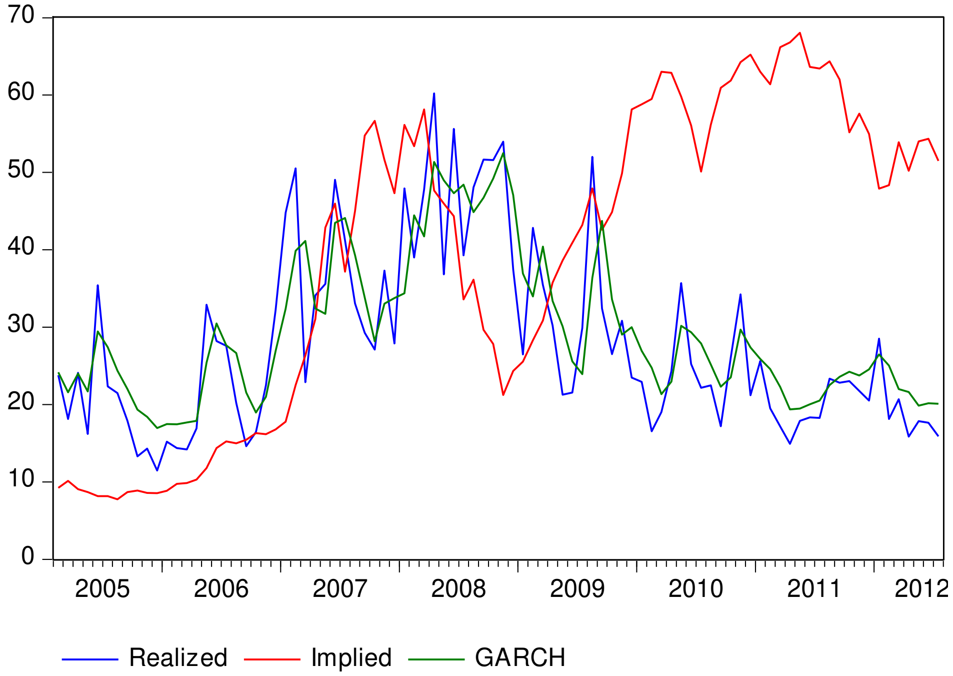

Fig. A4. Realized, Implied and GARCH volatility of China

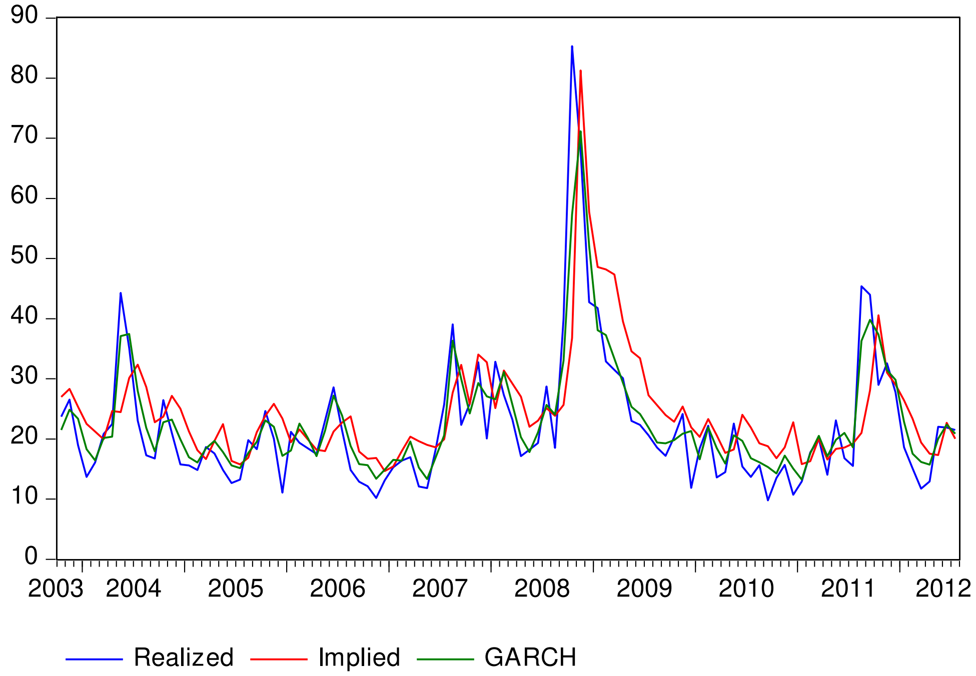

Fig. A5. Realized, Implied and GARCH volatility of Korea

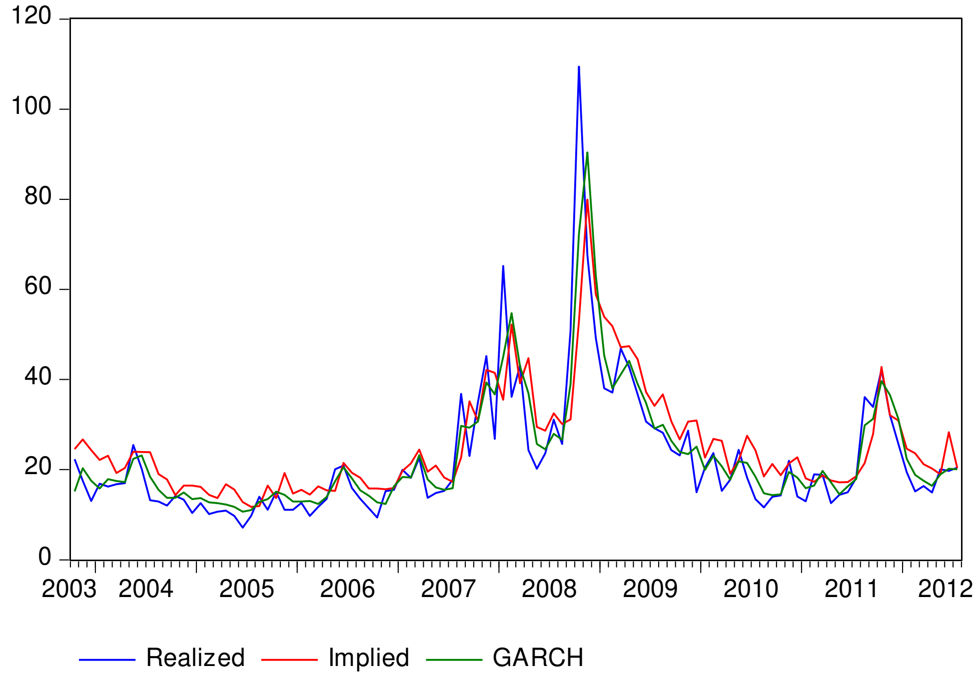

Fig. A6. Realized, Implied and GARCH volatility of Hong-Kong

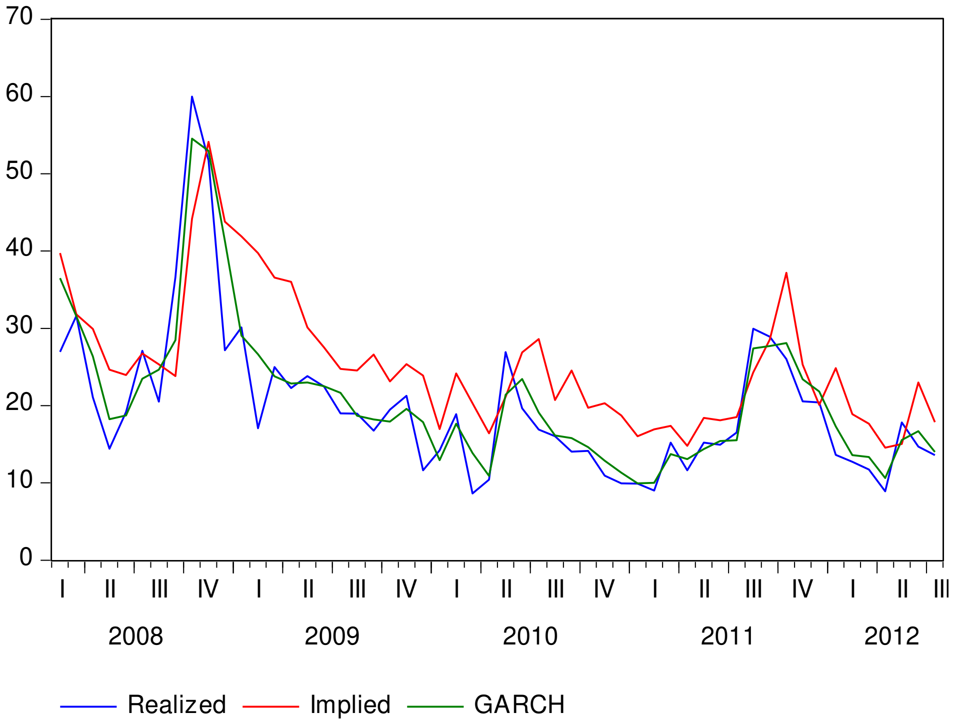

Fig. A7. Realized, Implied and GARCH volatility of Australia

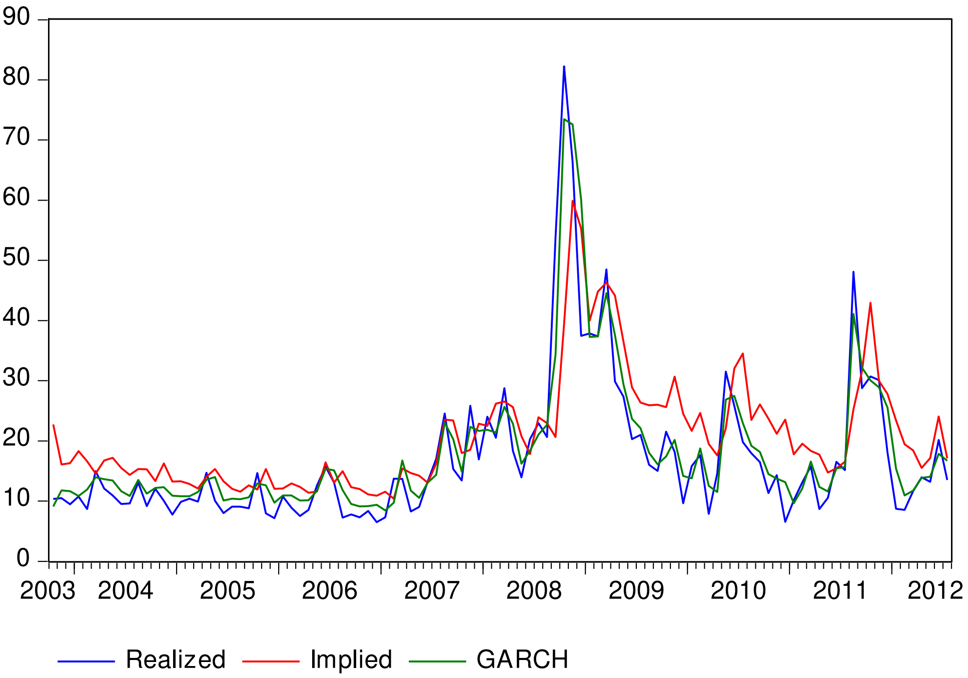

Fig. A8. Realized, Implied and GARCH volatility of US