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Comparison of the GARCH and stochastic models: An application to the Mexican peso-us dollar exchange rate

Comparación de modelos GARCH y estocásticos: una aplicación en el tipo de cambio peso mexicano-dólar estadounidense

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Abstract

Forecasting volatility is of great importance an important topic for researchers, entrepreneurs, and policymakers. This work compares different volatility models to ascertain their forecasting efficiency. The models include standard approaches such as Autoregressive Conditional Heteroskedasticity (GARCH), exponential GARCH, and Stochastic Volatility models (SV). For estimation, a comparison between the Frequentist and the Bayesian approaches are made using the maximum likelihood and the Monte Carlo Markov Chains (MCMC) methods. The case analysis considers the Mexican peso/US dollar exchange rate. The results show a favorable behavior between the SV models estimated with the MCMC and the GARCH models in forecasting out of the sample. Additionally, the analysis shows that the current volatility reacts to the data within the last period, despite the former periods.

JEL Code: C13, C32, C52, G17
Keywords: GARCH; Stochastic Model; Exchange rate

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Resumen

El pronóstico de la volatilidad es un tema importante para investigadores, empresarios y responsables políticos. Este trabajo compara modelos de volatilidad para determinar su eficiencia en el pronóstico. Los modelos incluyen modelos estándar, como los son, modelos de Heteroscedasticidad condicional autoregresiva (GARCH), exponencial y Volatilidad estocástica (SV). Para la estimación, se realiza una comparación entre los métodos frecuentistas y bayesianos, utilizando máxima verosimilitud y Cadenas de Marcov Montecarlo (MCMC). El análisis es aplicado en el tipo de cambio del peso mexicano-dólar estadounidense. Los resultados muestran que los modelos SV estimados con MCMC se comportan favorablemente frente a los modelos GARCH en el pronóstico de la muestra. Además, el análisis evidencia que la volatilidad actual reacciona a la última información dentro de un período, sin importar los períodos anteriores.

Código JEL: C13, C32, C52, G17
Palabras clave: GARCH; Modelo estocástico; Tipo de cambio

Introduction

Exchange rates play an important role in international trade, the determination of investments, business risk management, as well as in the economic situation within a country (Frankel and Saravelos, 2012; Korol 2014). The variations in currency prices are caused, in many cases, by imprecise and ambiguous factors such as economic, political and psychological conditions (Gabaix and Maggiori, 2015; Della Corte et al. 2016; Pinho and Couto, 2017). The above generates volatility, uncertainty, and risks for the economic agents that interact in financial markets.

Volatility is an important issue in regards to international decision-making, since the expected returns on prices and their high variability have a negative correlation. Therefore, high volatility generates a decrease in yields and significant losses for economic agents (Guo et al. 2014; Bali and Zhou, 2016; Morales et al. 2016). In this regard, some studies are oriented to know both the causes of these fluctuations and the alternatives to minimize uncertainty (Korol, 2014; Gupta and Kashyap, 2016; Lahmiri, 2017).

The difficulty of explaining and forecasting nominal exchange rate movements was systematically reported by Meese and Rogoff (1983); they considered their behavior as a random walk, which means that their growth rates are independent events. Similarly, Fama (1965) developed the efficient market hypothesis, which justifies the impossibility of predicting the returns of financial assets and also supports the idea that the stochastic process underlying the returns is a martingale process.

However, subsequent research has shown how the financial series cannot obey the ethical assumptions of these two proposals. Characteristics such as independence, identical distribution and normality may not appear in the series. Subsequently, the exchange rate series can present some stylized facts like non-linearity, non-normality, volatility clustering, asymmetry and heavy tails (Yang and Chen, 2014; Patton and Sheppard, 2015; Pinho et al. 2016; Byrne et al. 2016) which should be considered when modeling and forecasting volatility.

Most of the research efforts regarding price variability have focused on standard forecast models, where volatility is a key parameter, using conditional heteroskedasticity dependent on time (Korol, 2014; Pinho et al. 2016). This type of volatility models is called General Autoregressive Conditional Heteroskedasticity (GARCH), proposed by Engle (1982) and generalized by Bollerslev (1986) as an alternative to model non-linearity and volatility clusters in a simple way and easily adapting to different scenarios. Autoregressive models propose a better performance in terms of forecasting, and they are easy to combine with estimation methods (West and Cho, 1994; Lahmiri, 2017).

However, there is evidence arguing that GARCH models do not consider stylized facts of the financial series such as trends, heavy tails, and non-seasonality. Thus, stochastic models were proposed by Taylor (1986) whose main advantage is to consider a random component adaptable to abrupt changes. In stochastic models, the volatility estimation process is not directly observable and part of the equation that represents it is not completely known. To do this, an additional likelihood function must be constructed that captures the behavior of the collected data (Jacquier et al. 1994; Sandmann and Koopman, 1998). The likelihood function is the one that has made the difference between stochastic estimates in the last decade. On the one hand, proposals are using maximum likelihood (Ait-Sahalia and Kimmel, 2007; Abanto-Valle et al. 2017). Alzghool (2017) proposes quasi-likelihood and asymptotic quasi-likelihood approaches obtaining favorable results. On the other hand, Bayesian simulations have proven forecasting efficiency in numerous occasions (Raftery et al. 1997; Kastner et al. 2017). In stochastic volatility models, the Monte Carlo Markov Chains (MCMC) has been generally used in estimation due to its development in algorithms (Jacquier et al. 1994; Kastner and Fruhwirth-Schnatter; 2014; Kastner, 2016).

However, the two types of models implied time-varying volatilities with very different properties. To compare the differences, the literature has mainly focused on their forecasting performance (Rossi, 2013; Clark and Ravazzolo, 2015; Chan and Grant, 2016). Knowing the

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best model for a financial series is a fundamental issue for making decisions, especially in cases of emerging and free-floating economies where volatility tends to be recurring (Neumeyer and Perri, 2005; Rafi and Ramachandran, 2018). In this study, a comparison of some GARCH and SV models was made. The main objective is to know which model is best to explain the volatility of the Mexican peso-US dollar exchange rate in terms of minimizing the forecast error. This work is divided into five sections. The second section describes the traditional models used in price volatility. The third section describes the structure of the proposed models and presents the data used to calculate volatility. In the fourth section, the estimation of the models and a comparison of the two most efficient models to predict volatility are made. Finally, conclusions are presented and future studies are suggested.

Volatility models

This section presents a summary of the two traditional volatility models used in this study, in order to evaluate their efficiency.

The GARCH model

The GARCH model (Bollerslev, 1986) is a volatility model where the recent past data provides information on the variance of a period. Therefore, the value of the current forecast is based on past information. GARCH models have been used in different areas of volatility price forecasting, such as the price indices (Kim et al. 2016; Yao et al. 2017), oil prices (Klein and Walther, 2016; Kristjanpoller and Minutolo, 2016) and exchange rates (Trucios and Hotta, 2016; Gupta and Kashyap, 2016).

The GARCH models for log return series, are given by returns $r_t = log\left(\frac{x_t}{x_{t-1}}\right)$, let a_t is the innovation at time t, as $a_t = r_t - E_{t-1}[r_t]$. Then a_t follows a GARCH (p,q) model if $a_t = \sigma_t \epsilon_t$, where $\{\epsilon_t\}$ is a sequence of independent random variables with equal distribution, average 0 and variance 1, then the volatility model is represented as follows:

$$h_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 h_{t-1}^2, \quad (1)$$

where $\alpha_0, \alpha_1, \beta_1, \beta_2$ and $\alpha_1 + \beta_1 + \beta_2 < 1$. The variance process is always straightly positive and stationary.

The GARCH model family can be obtained from a transformation of the conditional standard deviation (SD) h_t determined by the transformation $f(\cdot)$ of the innovations a_t

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, and lagged transformed conditional SDs. This is, the conditional variance h_t^2 in a simple equation follows an AR (1) process. The GARCH (2, 1) model (in which h_t^2 follows an AR (2) process) allows a better variance dynamic, then we have:

$$h_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 h_{t-1}^2 + \beta_2 h_{t-2}^2. \tag{2}$$

As we have already noted, we assume that the parameters $\alpha_0, \alpha_1, \beta_1, \beta_2$ are all positive and $(\alpha_1 + \beta_1) < 1$.

The GARCH model assumes that positive and negative error variations have a symmetric effect on volatility, which means that good and bad news have the same effect on volatility. Patton and Sheppard (2015) show that future volatility is more strongly related to the volatility of past negative returns than to that of positive returns and that the impact of a price jump on volatility depends on the sign of the jump, with negative (positive) jumps leading to higher (lower) future volatility.

An exponential GARCH, EGARCH model (Nelson, 1991) assumes that if the distribution is symmetric, the change in the variance of tomorrow is conditionally not correlated with the excess of yields of today. Therefore, the asymmetry in a GARCH model can be calculated as follows:

$$h_t^2 = \alpha_0 + \beta_1 h_{t-1}^2 + \gamma \frac{\epsilon_{t-1}}{\sqrt{h_{t-1}^2}} + \omega \left[\frac{|\epsilon_{t-1}|}{\sqrt{h_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right], \tag{3}$$

where $\alpha_0, \beta_1, \gamma$ and are constant parameters. Since the coefficient is typically negative, positive return shocks generate less volatility than negative return shocks. The EGARCH (1,1) suggests an interesting metric to analyze the effect of the news on conditional heteroscedasticity.

In addition, other models have been proposed in asymmetric volatility, such as the QGARCH quadratic introduced by Engle (1990) and Sentana (1995), and the GJR model proposed by Glosten et al. (1993).

Stochastic models

Stochastic volatility models (SV) consider a random variable, in contrast to GARCH models in which the conditional variance is a deterministic function of the parameters and the past data. In financial areas, the SV models are applied in many variables such as inflation

(Chan, 2015; Diebold et al. 2017), price indices (Pinho et al. 2016; Pinho and Couto, 2017) and exchange rates (Kastner and Fruhwirth, 2014; Alzghool, 2017).

The basic stochastic model is represented as a linear space state model with logarithmic and chi-square perturbations, its volatility can be represented as an autoregressive AR (1) model. The first model is the standard stochastic volatility model SV (1) and it is represented as follows:

$$\begin{aligned} y_t &= exp\left\{\frac{h_t}{2}\right\}\sigma_\epsilon \varepsilon_t \qquad \varepsilon_t \sim N(0,1), \\ h_t^2 &= \mu + \phi h_{t-1} + \tau\eta_t \qquad \eta_t \sim N(0,1), \end{aligned} \tag{4}$$

where y_t is the response variable, h_t is the unobserved log-volatility of y_t. The use of more than one autoregressive process results in some extensions of the stochastic model. Considering an SV (2) the log-volatility h_t follows a stationary AR (2) process, that is:

$$h_t^2 = \mu + \phi h_{t-1} + \phi h_{t-2} + \tau\eta_t \qquad \eta_t \sim N(0,1). \tag{5}$$

Note that, the estimation process of stochastic volatility is not directly observable. Therefore, an additional likelihood function must be constructed to include the behavior of the collected data. Jaquier, et al (1994) proposes a Bayesian approach, using the Monte Carlo Markov chain (MCMC) technique where the posterior distribution of the parameters is sampled.

The MCMC creates a Markov process whose stationary transition distribution is specified through P (θ | Y), then runs a large enough number of simulations where the distribution of the current process is as close as possible to the stationary transition distribution, thus creating a posterior distribution (Salimans et al. 2015; Ravenzwaaij et al. 2018).

The simulation starts by taking a random draw z_0 from the initial distribution p(x | z) and then a random stochastic transition operator z_1 is applied. Then:

$$z_t \sim q(\frac{z_t}{z_{t-1}}, x).$$

By judiciously choosing the transition operator and applying it repeatedly, we have a result that converges to a posterior p(x | z) distribution with an optimal result.

A series of algorithms that carry out the basic idea of the MCMC method have been proposed; these generate a large number of repetitions in a short period of time. Among the most widely used algorithms are the Metropolis-Hasting algorithm (Lin et al. 2000; Doucet et al. 2015) and Gibss sampling (Roberts and Rosenthal, 2009; Billio et al. 2016). The MCMC method in stochastic models has been used for price volatility with good performance (Kim et al. 2017; Brix et al. 2018).

Data and model analysis

In order to analyze the efficiency of the models described in the previous section, a real case of the exchange rate market is considered. The data are the daily prices of the FIX exchange rate for the US dollar-Mexican peso, during the period 1994-2018. The information was converted to monthly data where the first data corresponds to April 1994 and the last date is October 2018. The prices are taken from the official website of the Mexican Central Bank - Banco de Mexico (BANXICO).

Note that volatility is a variable not directly observed in the market. Therefore, volatility was calculated as log-volatility (Kim et al. 1998; Chan and Grant, 2016; Gatheral et al. 2018). The price returns (R) of the currency are used, is the difference between today's price and yesterday's price logarithm. The formulation is as follows:

$$R = ln\left(\frac{p_t}{p_{t-1}}\right) \tag{6}$$

where p_t is the current period price and h_t^2 is the log-volatility analyzed, then log volatility is:

$$hR_t^2 = \left(R_i - \underline{R}\right)^2, \tag{7}$$

where $\underline{R}$ is the mean in price returns. Five volatility models were developed based on the traditional GARCH and SV models, then:

GARCH 1,1: $hR_t^2 = \alpha_0 + \alpha_1 aR_{t-1}^2 + \beta_1 hR_{t-1}^2$

GARCH 1,2: $hR_t^2 = \alpha_0 + \alpha_1 aR_{t-1}^2 + \beta_1 hR_{t-1}^2 + \beta_2 hR_{t-2}^2$

EGARCH: $hR_t^2 = \alpha_0 + \beta_1 log\left(hR_{t-1}^2\right) + \gamma \frac{aR_{t-1}}{\sqrt{hR_{t-1}^2}} + \omega\left[\frac{|aR_{t-1}|}{\sqrt{hR_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right]$

SV 1: $hR_t^2 = \mu + \phi hR_{t-1}$

SV 2: $hR_t^2 = \mu + \phi hR_{t-1} + \phi hR_{t-2}$

Finally, parameter estimation was calculated as follows: GARCH (1,1), GARCH (2,1) and EGARCH were estimated by maximum likelihood with a normal distribution. SV (1) and SV (2) using an exponential distribution and a prior function for hR_{t-1}, $N(0,1)$, and for μ, $N(0.0012,0.1)$.

Results

Models results

First, the GARCH models were developed and then compared, in order to select the best one considering some criteria. The Akaike information criterion (AIC) (Akaike, 1974) is a technique based on a sample fit to estimate the likelihood of a model to predict future values. A good model is the one that has minimum AIC among all the other models. The Schwarz Criterion (SC) (Schwarz, 1978) considers both, the closeness of fit of the points to the model and the number of parameters used by the model. Using this criterion, the best model is the one with the lowest SC.

Table 1
Analysis of results in GARCH models

Model	Model parameters	Parameters significance	Akaike info criterion	Schwarz criterion
	α_0 =0.000433	0.0000		
GARCH (1.1)	α_1=0.465281	0.0000	-4.314630	-4.264637
	β_1=0.128459	0.0303		
	α_0 =0.000434	0.0000		
GARCH (2,1)	α_1=0.459434	0.0000	-4.314609	-4.252118
	β_1=0.208128	0.0273		
	β_2=-0.073937	0.1361		
	α_0 =-3.428093	0.0000		
EGARCH	β_1=0.215611	0.0005	-4.403681	-4.341190
	γ =0.483839	0.0000		
	ω =0.553491	0.0000		

The results in Table 1 show that the EGARCH model has the minimum AIC and minimum SC. However, the parameter α_0 is negative, then the assumption of positivity is not met. Therefore, the best model that met the criterion s is the GARCH (1, 1).

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To estimate the parameters of the SV models, the Metropolis Hasting algorithm (Metropolis et al. 1953; Hasting, 1970) is used. Monte Carlo standard error (MCSE) is a standard deviation around the posterior mean of the samples. The acceptable size of the MCSE depends on the acceptable uncertainty, then when we compare models, a lower MCSE is better (Flegal et al. 2008).

Table 2
Analysis of results in SV models

Model	Model parameters	Montecarlo standard error parameters	Max Efficiency MCMC
SV (1)	μ=0.0009798	0.00097	0.1342
	ϕ=0.2209891	0.00169	
SV (2)	μ=0.0007921	0.00001	0.1032
	ϕ =0.183780	0.00215	
	ρ =0.172050	0.00209	

Table 2 presents the resulting parameters of stochastic models. The Monte Carlo standard error shows that the parameter μ is better in the second model, but the rest of the parameters are more significant in the first model. The efficiency MCMC demonstrates that SV1 is the best model with 13.42%.

Comparison of models

In this section, the GARCH (1, 1) and the SV (1) models are compared in the forecast for the next seven periods. It is observable that the following period which corresponds to November 2018 is a period of high volatility, while the fourth period which corresponds to February 2019 shows low volatility. We use aR and hR that were calculated previously on dependent variables. To calculate and analyze the errors in forecasting, we use the Mean Absolute Deviation (MAD), the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE) methods (Franses, 2016; Khair et al. 2017). The results are in Table 3.

The error indicators show that the SV1 model minimizes the error for forecasting in periods of instability (high or low volatility). It is observable that it minimizes the absolute error in all periods except for the last two. The squared error is small in the stochastic model for most periods, except in periods five and six.

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The global results in MAD, RMSE, and MAPE are smaller in the SV1 model than in the GARCH (1.1) model. Therefore, the SV1 model is considered as the best model to predict the variability in the exchange rate of the outside sample.

Table 3

Forecast analysis

	Period	Value	Real log-volatility	Absolute error	Squared error	Percentage error	MAD	RMSE	MAPE
	1	0.00051	0.00232715	0.00182	3.313E-06	0.78			
	2	0.00158	0.00018830	0.00139	1.939E-06	7.40			
	3	0.00072	0.00340258	0.00268	7.176E-06	0.79			
GARCH (1,1)	4	0.00211	0.00000002	0.00211	4.448E-06	91872.1	0.00135	0.00422	13132.6
	5	0.00070	0.00002223	0.00068	4.647E-07	30.67			
	6	0.00053	0.00041893	0.00011	1.319E-08	0.27			
	7	0.00070	0.00003959	0.00066	4.315E-07	16.59			
	1	0.00098	0.00232715	0.00135	1.81E-06	0.578			
	2	0.00149	0.00018830	0.00131	1.71E-06	6.934			
	3	0.00102	0.00340258	0.00238	5.67E-06	0.700			
	4	0.00173	0.00000002	0.00173	3.00E-06	75433.1	0.00133	0.000002	10787.4
SV1	5	0.00098	0.00002223	0.00096	9.17E-07	43.081			
	6	0.00098	0.00041893	0.00057	3.20E-07	1.351			
	7	0.00107	0.00003959	0.00103	1.07E-06	26.089			

Conclusions

The exchange rate is a financial variable difficult to predict due to the different inaccuracies that may occur over time. Nevertheless, literature models have proposed a way to know the future volatility. GARCH and SV models have been commonly used for forecasting and estimating volatility. However, no consensus has been reached on which is the best proposal.

This work proposes a comparison between some fundamental models, GARCH and SV. The analysis concluded that the SV model works better than GARCH models; both were used to out-of-sample forecasting volatility of the exchange rate. The results show a decrease in the forecast error in most of the periods analyzed when the stochastic model is used.

In addition, the analysis found that the models of volatility in the series are effective only when the past information is only a period back, because when the models consider two lags their effectiveness decreases. In this sense, both the GARCH and SV models show better adjustments when they only consider a period lag.

Finally, it is suggested that in future research, the functional SV model can be extended in order to minimize the error.

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