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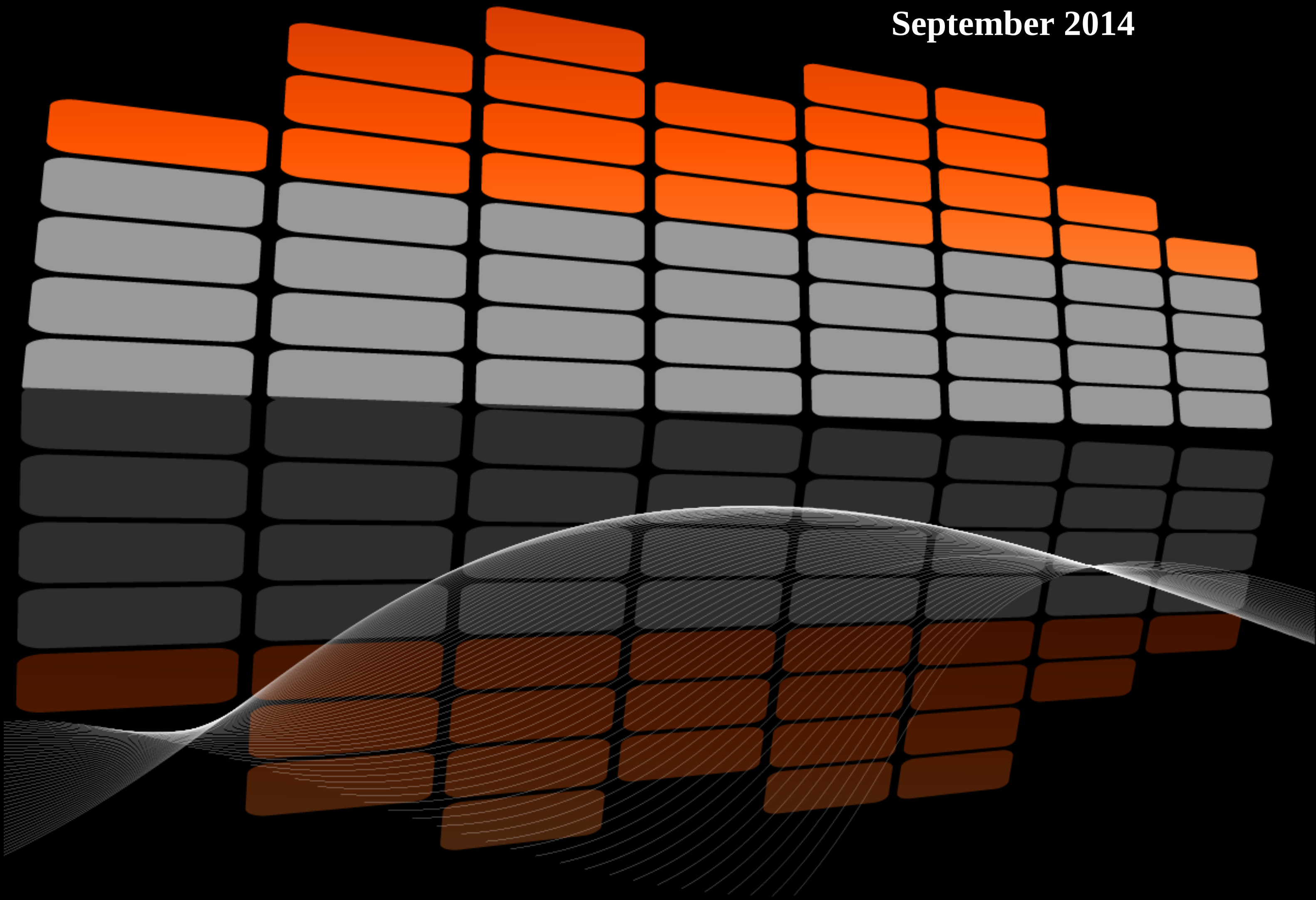

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This issue is dedicated to

Applied Financial Research

Guest Editor for this number:

Prof. Nuno Ferreira (ISCTE-IUL)

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Editorial Note
"Applied Financial Research". Financial markets - A need for Reflection

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This number of the IJLTFES - International Journal of Latest Trends in Finance and Economic Sciences is dedicated specifically to Financial Markets and financial issues and to the discussion involving methodologies on the area of "Applied Financial Research".

First of all, we would like to thank on behalf of the IJLTFES, to Prof. Nuno Ferreira (ISCTE-IUL), for his contribution as Guest Editor for this number of the Journal.

After this recognition, it is appropriate to thank also to all the authors for their contributions to this Journal's issue. A specific reference to the authors' work, article by article, will be made in order to get an advanced envision of their contributions in the discussion of these matters on the area under analysis on this issue.

Considering the potential and real effects of the decision making related to this topic, financial markets get central in the global economic system. The global economy is going systematically depending on what happens in financial markets environment. The recent crisis, in course for several years, maintains the global economy in a slow economic growth rhythm. This current situation shows the important of a theoretical discussion and the need of fresh academic approaches in order to get solutions for a new context in the global markets.

Financial markets are nowadays significantly discussed and marked for fast changes on short term trends, which are depending on multiple factors that in current times are very active in the markets, whichever they are, in the area under analysis, i.e. the financial area. Presently, many troubles happen systematically in the markets, demanding for a broad discussion and a large debate in the most different *fora*. The financial markets bases have been questioned by academicians; and politicians are systematically confronted with new facts and they look lost in front of the changing reality resulting from often inadequate measures and mistaken economic politics. Theoretical foundations on finance and mainstream approaches are often away from reality and new paradigms seem to be necessary. In this number, methodologies are presented and a debate around trends and adequacies is explored, with approaches looking for attempts of getting solutions for financial problems and to explain the financial markets as much as proposing information and guidelines for investors and for decision makers in general.

This number first presents the paper "Forecasting the Direction of BIST 100 Returns with Artificial Neural Network Models", by Süleyman Bilgin Kılıç, Semin Paksoy and Tolga Genç. On this paper, Artificial Neural Networks (ANN) models were used to forecast the direction of Borsa Istanbul 100 (BIST100) index returns. The study of these authors combined three ANN models to analyze BIST 100 returns. Weekly time-lagged values of exchange rate returns, gold price returns and interest rate returns were used as inputs to ANN models in the training process. Results of their study showed that BIST100 index returns follow a specific pattern in time. The composite use of ANN models provided to the authors the possibility to demonstrate that there is a valuable information about weekly direction of BIST100 index return given the information of present BIST100 index return, allowing valuable information to the investors although the BIST100 stock market does not demonstrate to be fully informational efficient.

Follows then a study from Rocha, Souza, Santos and Ferreira entitled "Box-Jenkins and Volatility Models for Brazilian 'Selic' Interest and Currency

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Rates". The authors use statistical models for the analysis of macroeconomic variables that considered of crucial importance. The authors used these models to describe the behaviour of Brazilian SELIC interest rates and foreign exchange for long periods since the seventies of last century. To accomplish this objective Rocha et al used the Box-Jenkins methodology. They analyzed the residues that showed the presence of heteroscedasticity. A joint model was used to estimate the mean process by an ARIMA and the conditional variance by ARCH, GARCH, TARCH, EGARCH models. The results showed SELIC interest rate series. Evidence was shown that there is asymmetry in the variables, yet there was a leverage effect. In addition, the volatility of these series in the context of Brazilian economic scenario reveled the face of external and internal crises in the examined periods. So, the fitted models effectively captured the Brazilian economic behaviour during the period comprehended from 80´s to 90´s showing the mid degree of persistence of shocks like bad and good news, aiding to understand the performance of these variables providing decision-making to managers, to act in long and short term. The authors conclude also that either internal or external economic crises affect the conduct of Brazilian monetary and fiscal policy and may alter the expectations of other economic agents.

Follows a paper from Pinto and Borges "The Banking Crisis of 2007-2008, and Contemporary Responses", discussing the recent banking crisis initiated in 2007, the strong impact in the economic activity and the responses needed at several levels to face all the impacts. The authors finish their paper by saying that "… what the financial crisis of 2007-2008 showed us all, is that we do need different rules to promote financial stability, than those we had under Basel II", what shows the importance of the regulation and its impact on the financial system stability as much as its importance on the economic activity as a whole.

By its turn, the paper "Modeling long memory in the EU stock market: Evidence from the STOXX 50 returns", by Bentes and Ferreira, shows the importance of modeling long memory in stock markets in order to get conclusions on this kind of analysis. The authors show that the FIGARCH model is the best model to capture linear dependence in the conditional variance of the STOXX 50 returns as given by the information criteria. Their paper analyzes whether the STOXX 50 returns exhibit persistence in the conditional variance equation. They estimated the GARCH, IGARCH and FIGARCH models based on a data set comprising the daily returns for the period from January 5th, 1987 to December 27th, 2013. Their results confirmed that the long-memory in the volatility returns constitutes an intrinsic and empirically significant characteristic of the data. At the practical level, the authors compared their results with the ones of previous studies and showed that they were in consonance with the evidence showed by them on this subject.

The paper "PSI-20 Portfolio Efficiency Analysis with SFA", by Ferreira, Souza and Souza, investigates the technical efficiency of the individual companies and their respective groups of the Portuguese stock market. In order to get results from the study, the authors combined the input variables "market value and return" with exogenous variables such as "interest income", "depreciation", "cost of goods", "employees" or "net sales" in a Stochastic Frontier Analysis Model. The technical efficiency of the PSI-20 enterprises index was estimated by getting the factors which influence efficiency variability, applying the SFA approach main improvement which lies in its potential to categorize between measurement error and systematic inefficiencies in the estimation process. The results revealed that the technical efficiency is higher for the enterprises placed in the industry, construction and distribution economic sectors whereas the commercial banking sector has the lowest technical efficiency scores. The "employees" and "depreciation" variables were the elements that most enhance to the stock market inefficiency.

The last paper on this issue is a Book Review by Ferreira, M. A. M.. It is appropriate to mention that IJLTFES has been chosen for some book reviews in which the main summarized conclusions of the reviewed books are highlighted. The book "Network Models in Economics and Finance", 978-3-319-09683-4, vol. 100 is a volume from Springer Series "Springer Optimization and Its Applications". Valery A. Kalyagin, Panos M. Pardalos, Themistocles M. Rassias are the Editors of this book which - as the editors refer and as cited in this paper by Ferreira - contains new tools for financial data mining and offers a discussion about the uncertainty of the network market analysis; provides as well a network analysis to the financial crises; includes methods of network analysis applied to corporate governance and investment tools. The author of this review mentions the broad range of the subjects dealt with in the reviewed book and also on the analytical tools used and described. According to Ferreira, the subjects that are a substantial part of this book are devoted to the Financial Markets which are very determinant to the World Economy. In short, Ferreira concludes that this is a book of indispensable reading for senior and beginner researchers and professionals in economics, financial management and network analysis.

The papers published on this issue show the importance of analyzing the financial markets and offer a contribution for a better understanding of multiple situations in which modeling permits the analysis of trends and the behavior of agents. The agents' decisions on this area have determinant effects on the economic system as a whole and their analysis reveals to be considered essential for the correct planning of individual activities of agents on this context and a correct understanding of the markets as a whole. Although many different branches of science develop studies in this area to better understand the human financial decision making processes, the models presented in this number make a strong contribution for the understanding of financial markets and agents decisions on these markets as much as for the financial markets' modeling, itself.

Forecasting the Direction of BIST 100 Returns with Artificial Neural Network Models

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Abstract **- In this paper, Artificial Neural Networks (ANN) models are used to forecast the direction of Borsa Istanbul 100 (BIST100) index returns. Weekly time-lagged values of exchange rate returns, gold price returns and interest rate returns are used as inputs to ANN models in the training process. Results of the study showed that BIST100 index returns follow a specific pattern in time. Estimated ANN models provide valuable information to the investors and that BIST100 stock market is not fully informational efficient.**

*K**eywords** Stock Return, Forecasting, BIST100 index, Artificial Neural Networks, Back Propagation*

1. Introduction

Forecasting the direction of stock return has been regarded as highly complicated and difficult process since stock market is dynamic and chaotic in nature (Kara et al., 2011). Predicting the market price movements and forecasting the projections about future are the challenging applications. Many micro and macro economic factors interact with the stock market prices. Forecasting empowers the inventors to the existing historical data to predict and evaluate investment instruments and their directions/movements (Hadavandi et al., 2010). This is essential for the investors to make best choice among the investment instruments.

The main objective of stock market prediction is to achieve best results using minimum required input data and the least complex stock market model (Hadavandi et al., 2010). An increasing interest of professional investors in the firm's common stock will cause positive adjustments in the market price of the firm's common stock (Jones and Litzenberger, 1970). Umstead's study in 1977, one of the oldest studies, had undertaken an extensive statistical investigation of aggregate quarterly stock prices (the Standard and Poor's Index of Five Hundred Common Stocks) and their relationship to a leading indicator of business activity. The Box-Jenkins methodology is utilized to build a transfer function model relating changes in the National Bureau of Economic Research Leading Composite Index to subsequent stock price changes. The model is tested in a fifty quarter holdout sample and found to be successful at forecasting stock price changes one quarter ahead. The study (Akcan and Kartal, 2011), containing stock prices of seven companies which form Insurance Sector Index tried to be estimated with ANN models. Their results showed that all the predictions were generally good, but especially up to one month are quite successful in forecasting.

Over the years, many researchers have been focused on the methods to improve the accuracy of predictions of index value and returns of stock prices in developed and developing countries. According to an extensive literature investigation, it is appeared that many methods and algorithms are examined to promise more accurate prediction in stock market indices. Some of them are regression model, support vector machine algorithm (Liu and Hu, 2013; Xiong et al., 2014; Kazem et al., 2013), neural network (Salehi et al, 2011), data mining (Nemeş and Butio, 2013), fuzzy clustering method (Li et al., 2013) and hybrid methods (Hsu, 2013). Since the stock price time series data is characterized by nonlinearity, discontinuity and highly frequency polynomial components, predicting the stock price or its movements can be categorized as np-hard (non-deterministic polynomial) problem. These types of problems, including parameterized complexity, are more complex and impossible to solve by classical models. Therefore genetic algorithms, ANN, fuzzy logic and vector machine algorithms are examined

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for predicting the stock price or its movements. These methods may provide a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information.

Many studies used different variables such as exchange rates, daily US dollar returns and oil prices in forecasting returns of investment instrument by ANN model (Zhang and Berardi, 2001; Kılıç, 2013; Farahani and Mehralian, 2013). Results of these studies imply that the degree of predictability of ANN can be considered as potentially useful for investors.

In some studies, results of the several methods such as regression and time series models had been compared with the neural network by using the same data. While comparing ANN with regression, AR, ARMA, SARIMA and GARCH models, neural network proved to be a better predictor but SARIMA performed better than ANN for mid-term and long term forecasting. It was opposite in short term forecasting and the Bayesian Chiao's model is much better than ANN (Carvalhal and Ribeiro, 2007; Kyung et al., 2008).

Some other studies are aimed to forecast the stock price returns and direction of their movements. ANN has become one of the most popular forecasting models in capital market studies over the last few years. In the studies, various types of ANN models were used to predict stock market prices (Nemeş and Butio, 2013; Cao et al., 2011; Kara et al., 2011; Hadavandi et al., 2010), stock price index (Kyung et al., 2008; Hosseini et al., 2011), their returns (Reboredo et al., 2012; Ferreira and Santa-Clara, 2011) and trends/the future movements (Cao et al., 2011; Kara et al., 2011; Merh, 2013).

Past studies were generally attempt to predict the returns by using past historical value of one kind of investment instruments. However, stock market prices or returns are generally influenced with the other investment instruments as previously mentioned. In the recent years, researchers have investigated the effects or relationships of various variables on stock returns and stock market indices. For instance, influence of currency rates on stock market (Morelli, 2002; Brown and Otsuki, 1993) and impact of multi variables (inflation rates, oil prices, gold prices, growth rates) on stock market indices (Dastgir and Enghiad, 2012); and relationships between oil price and stock returns (Jones and Kaul, 1996), inflation rates and stock returns (Mc Queen and Roley, 1993) are some of these studies.

The main objective of this article is to predict the direction of BIST100 index returns by using the lagged value of exchange rate returns, gold price returns and interest rate returns as input to ANN models. In recent years, several studies have used many techniques and variables to predict the future movements of stock market index, their directions and returns. But there are limited studies that use other investment instruments as inputs in the back propagation learning stage in the ANN algorithm. In this study, we have used a feed-forward back propagation artificial neural network (BPANN), a powerful system, capable of modeling complex relationship between variables, based on supervised procedure. With this respect, this study contributes to the literature of forecasting of stock market return.

The rest of this article is organized as follows. Section 2 refers to the description of ANN method, section 3 includes the sample selection, methodology and empirical results and finally section 4 concludes the article and discusses some future research perspectives.

2. Artificial Neural Network

ANN has been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by Mc Culloch and Pitts (1943).

The inspiration of ANNs comes from the desire to produce artificial systems capable of performing sophisticated a computation similar to a human's brain performs. Thereby ANN resembles the brain and provides the solution based on the representative set of historical relationship (Papale, 2003). The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm (Abraham, 2005).

ANN is a popular artificial intelligence model used to acquire knowledge from datasets in different domains by applying learning techniques which work as estimators between the available inputs and the desired outputs (Gannous and Elhaddad, 2011). The units, often organized in layers, are connected by communication channels (connections) and operate only on their local data and on the input they receive via the connections.

The ANN consists of different layers. The input layer takes the input data then distributes it to the connections which connect the hidden layer and the input layer. The neurons in the hidden layers process the summation of the information received from the connections of the input layer. Then it processes the summations with its activation function and distributes the result to the next layer. This process continues down through the layers to the output layer. The neurons of the output layer process the summation of the information received from the connections of the hidden layer. Then each neuron processes the summation with its activation function. The output of the activation function is the output of the ANN (Desrosiers, 2013).

The learning phase of the ANN can be supervised or unsupervised. Supervised learning consists of giving inputs to the ANN and adjusting the weight to minimize the sum of the differences between the predicted output given by the ANN and the desired output (Desrosiers, 2013).

The accumulated operating data used in ANN training may contain corrupt and noisy data records. Therefore, to enhance the reliability of the trained ANN, a data preprocessing technique is necessary for preparing the training and testing data set (Gannous and Elhaddad, 2011, p.124). Furthermore, suitable data processing technique increases the performance of learning stage and performance of ANN.

3. Sample and Methodology

3 1 The Sample and Variable Selection

In this study, up to forth (4 week) lagged value of weekly returns of interest rates, dollar exchange rates and gold price are used as input variables in ANN models in order to predict weekly directional movements of BIST100 index value. The input and output variables are shown in Table 1. The output of the ANN models is defined by the following function;

$$BIST\_Dir = \begin{cases} 1, & if\ return > 0 \\ 0, & if\ return \leq 0 \end{cases}$$

Weekly returns of dollar exchange rate and gold price are calculated by the following equation;

$$R_{k,t} = \frac{(P_{k,t} - P_{k,t-1})}{P_{k,t-1}} \quad (1)$$

Here, $R_{k,t}$ and $P_{k,t}$ represent weekly return of relevant kth (k=1,2,3,4) investment instruments and weekly closing price of the kth instrument respectively, and t denotes the time lag.

The sample data covers 606 weekly returns between the period of January 01, 2002-October 11, 2013 which were obtained from the electronic data delivery system of the Central Bank of Turkey.

Table 1. Sample Data

Input	Variable	Description
	IRate	Weekly weighted average interest rates, applied to Turkish lira deposits
	DRate	Weekly percentage changes in U.S. dollar exchange rate according to the closing price
	GRate	Weekly percentage change in gold price according to the closing price
	BISTRate	Weekly percentage change of BIST100 index according to the closing value
Output	BIST_Dir	Weekly directional movement of BIST100 index value

3 2 Training of the ANN models

After performing so many experiments, we trained three ANN models; Model(0), Model(1) and Model(0,1), Inputs of the all there ANN models are first, second, third and forth lagged value of investment instruments (IRate, DRate, GRate). First lagged value of BISRate input changes according to the model. Model (0) covers only negative returns; Model(1) covers only positive returns and Model(0,1) covers both positive and negative returns respectively. Output of the all there ANN models are in boolean type (BIST_Dir= 0, BIST_Dir= 1). Here, 0 and 1 represents negative and positive direction.

The ANN models trained as follows;

Let $R_{k,i}$ (i=1,…,16.) denotes first, second, third and forth lagged values of investment instruments (IRate, DRate, GRate and BISTRate) which are used as input in the input layer; i, j and k represent input, hidden and output layers; n, m and p indicate number of nodes in input, hidden and output layers respectively. Each hidden node j produce an output by using following logit (sigmoid) activation function $f\ (x_j)$ which uses the weighted sum of the inputs R_i from the input layer;

$$f(x_j) = 1/(1+e^{-z_j}),\ z_j = \sum_{i=1}^{n} w_{ij} R_i,\ j = 1,\ldots,m. \qquad (2)$$

Here, w_{ij} is connection weights from input node i to hidden node j. The outputs from the hidden layer nodes are the inputs of the output layer nodes. Also, each output node k produce an output by using following sigmoid activation function $f\ (x_k)$ which uses the weighted sum of the inputs $f\ (x_j)$ from the nodes of hidden layer;

$$y' = f(x_k) = 1/(1+e^{-z_k}),\ z_k = \sum_{j=1}^{m} w_{jk} f(x_j),\ k = 1,\ldots,p. \qquad (3)$$

Here, y' denotes predicted value of the ANN model ($0 \le y' \le 1$), w_{jk} is connection weights from hidden node j to output node k. Hence, the prediction error ($\varepsilon_t = y_t - y'_t$) is the difference between the actual status (y_t) which is either 0 (for negative return) or 1 (for positive return), and predicted direction of BIST100 return value (y'_t) in week t.

Hence, the total prediction error function of ANN given the training sample size of N is;

$$S(w) = \sum_{t=1}^{N} \varepsilon_t^2 \qquad (4)$$

Values of the all weights $(w_{ij},\ w_{jk})$ in the ANN model were determined by the following estimation algorithm:

All weights were assigned with random values initially and modified by the gradient descent algorithm according to the gradient vector of the total prediction error function;

$$w_{new} = w_{old} + \alpha \nabla E(w)\big|_{w_{old}},\ \nabla E(w) = (\partial S(w) / \partial w) \qquad (5)$$

α is the learning parameter ($0 \le \alpha \le 1$), and taken as α=0.0001 in this study. Iterations eventually terminated at a local minimum of the total prediction error function when $w_{new} \cong w_{old}$.

Table 2. Parameter Estimation of Model (1)

Predictor		Predicted		
		H(1:1)	H(1:2)	H(1:3)
Input Layer	(Bias)	-0,213	-0,382	-0,230
	IRate1	-0,469		0,219
	IRate2	0,046	-0,343	0,238
	IRate3	0,422	-0,151	0,000
	IRate4	0,258	0,050	0,156
	GRate1	-0,303	0,440	-0,220
	GRate2	-0,159	0,533	-0,158
	GRate3	0,103	-0,268	-0,052
	GRate4	-0,061	0,100	0,327
	$DRate_1$	0,366	0,369	0,165
	$DRate_2$	-0,092	-0,330	0,161
	$DRate_3$	0,228	-0,285	0,020
	$DRate_4$	0,249	-0,404	-0,418
	$BISTRet_1$	-0,270	0,017	0,487
	$BISTRet_2$	-0,032	-0,114	0,318
	$BISTRet_3$	0,175	-0,489	0,092
	$BISTRet_4$	0,125	0,068	-0,021
Hidden Layer 1		BIST_Dir=0		BIST_Dir=1
	(Bias)	-0,585		-0,148
	H(1:1)	0,028		-0,419
	H(1:2)	0,241		-0,304
	H(1:3)	-0,083		-0,056

After the training process we obtained the adjusted connection weights for Model (1) in Table 2. The connection weights of Model (0) and Model (0,1) are not presented here.

Here, for example connection weights between input node $IRate_2$ (second lag value of interest rate and hidden layer node H(1:1), H(1:2) and H(1;3) are 0.046, -0.343 and 0.238 respectively. Weights between hidden layer node H(1:1) and output node BIST_Dir=0 and BIST_Dir=1 are -0.585 and -0.148 respectively. The other connection weights in Table 2 can be interpreted in similar way.

Table 3 gives observed and predicted classification results of weekly direction of BIST100 returns by the estimated three ANNs model. Classification results are given for the training and testing sample. In the study the whole sample data were randomly divided two equal groups as training and testing sample; training sample was used to train (estimate) the models, testing sample was used to evaluate the models in terms of the classification achievements.

Table 3. Classification Achievement of Estimated ANN models

Observed		Predicted BIST_Dir 0	1	Correct classif.
Model (0)				
Training	BIST_Dir= 0	93	7	93.00%
	BIST_Dir= 1	84	8	8.70%
	Overall Percent	92.20%	7.80%	52.6%
Testing	BIST_Dir= 0	41	1	97.60%
	BIST_Dir= 1	23	5	17.90%
	Overall Percent	91.40%	8.60%	65.70%
Model (1)				
Training	BIST_Dir= 0	4	87	4.40%
	BIST_Dir= 1	3	151	98.10%
	Overall Percent	2.90%	97.10%	63.30%
Testing	BIST_Dir= 0	3	27	10.00%
	BIST_Dir= 1	2	58	96.70%
	Overall Percent	5.60%	94.40%	67.80%
Model(0,1)				
Training	BIST_Dir= 0	107	106	50.20%
	BIST_Dir= 1	72	190	72.50%
	Overall Percent	37.70%	62.30%	62.50%
Testing	BIST_Dir= 0	22	28	44,00%
	BIST_Dir= 1	13	59	81.90%
	Overall Percent	28.70%	71.30%	66.40%

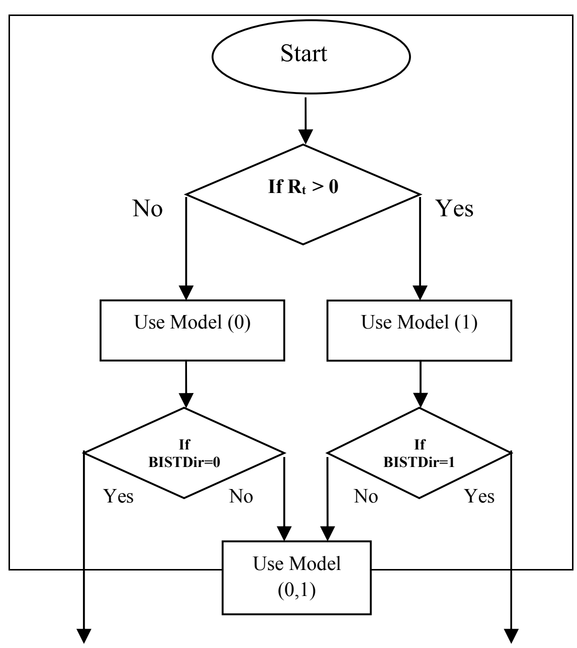
Dependent Variable: BIST_Dir

In last column of Table 3 for the testing sample we can see that if the present week return of BIST100 is non-positive, the Model (0) predicts next week as non positive direction 97.6% correctly for testing sample. If the present return is positive, the Model (1) predicts next week positive direction 96.7% correctly. However, the Model (1) does not predict negative direction (10%) accurately. At this situation, there is no matter whether the present return is either positive or non-positive, the Model (0,1) correctly predicts next week non-positive return 44% and positive return 81%. In order to eliminate these unreliable predictions and to make more accurate prediction, the three models can be integrated together for the prediction process.

Flowchart of integrated use of these models in prediction process is given in Figure 1. If the present return is positive the Model (1) should be used. If the Model (1) predicts positive return, prediction is 96.7% correct, stop the prediction. If the Model (1) predicts non-positive return do not use model (1); use model (0,1). If Model (0,1) predicts positive direction its prediction is 81.9% correct, stop prediction. If Model (0,1) predicts non-positive direction it is 44% correct, stop prediction.

If the present return is non-positive the Model (0) should be used. If the Model (0) predicts non-positive return, prediction is 97.6% correct, stop the prediction. If the Model (0) predicts positive return, use Model (0,1). If Model (0,1) predicts positive direction, prediction is 81.9% correct and stop prediction. If Model (0,1) predicts negative direction, prediction is 44% correct and stop prediction.

This result indicates that BIST 100 stock market is not fully informational efficient. In another words, Efficient Market Hypothesis (EMH) does not hold for the BIST stock market. The first level of EMH is the "weak" form which asserts that all past market prices and information are fully reflected in securities prices. Hence, technical analysis is of no use. The second level is the "semi-strong" form asserts that all publicly available information is fully reflected in securities prices. So, fundamental analysis is of no use. The third form is "strong" form asserts that all information is fully reflected in securities prices. In other words, even insider information is of no use. Estimated ANN models in this study provide valuable information about weekly direction of BIST100 index return. As an average integrated use of the three models provides 66.63% correct prediction for the direction of returns. This means that if an investor determines his/her weekly buying-selling strategy according to the prediction of the integrated ANN models, his/her weekly investment strategy will be profitable 66.63% of the time in the long run.



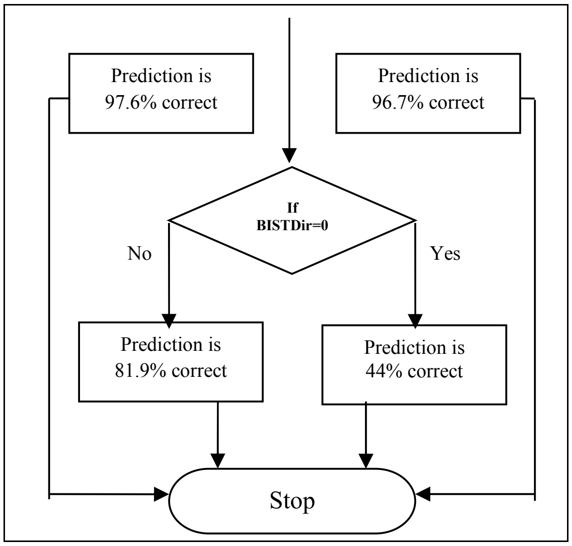


Figure 1. Flowchart of using the three combined models for prediction

4. Conclusion

This study combined three ANN models. Composite use of ANN models provides valuable information about weekly direction of BIST100 index return given the information of present BIST100 index return. Results of the study indicate that BIST100 returns follow a specific pattern in time. Generally positive returns follow positive returns and negative returns follow negative returns. Model (1) is used when present return is positive, Model (0) is used when the present return is negative and Model (0,1) is used when the prediction of previous two models are not accurate. Composite use of ANN models provides valuable information about weekly direction of BIST100 index return given the information of present BIST100 index return.

Similar further analysis can be performed for the returns of individual common stocks. This study uses weekly returns because of data availability restrictions. Further similar analysis can also be performed by considering returns of smaller time intervals, such as an intraday hourly change if the researchers can obtain available data. Hence, using small time intervals may provide more information.

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Box-Jenkins and Volatility Models for Brazilian 'Selic' Interest and Currency Rates

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Abstract – **The use of statistical models in the analysis of macroeconomic variables is of principal importance since these models support the economic theory, as well as represent the actual behaviour of these variables. In this context, this research has as objective to describe the behaviour of Brazilian SELIC interest rates and foreign exchange from January 1974 to February 2014 and from January 1980 to February 2014, respectively. To accomplish this objective the Box-Jenkins methodology was used, where the analysis of residues showed the presence of heteroscedasticity. Then joint modelling was used to estimate the mean process by an ARIMA and the conditional variance by ARCH, GARCH, TARCH, EGARCH models. The results obtained showed SELIC interest rate series, was modelled by an ARIMA (1,1,1)-EGARCH (3, 1, 1) and, to the exchange rate the modelled fitted was an ARIMA(0,1,1)-EGARCH(1,1,1). It is evidenced through these models that there is asymmetry in the variables, yet there was the leverage effect. In addition, the volatility of these series in the context of Brazilian economic scenario revel the face of external and internal crises in the periods examined. So, the models fitted effectively captured the Brazilian economic behaviour during the period comprehended from 80´s to 90´s showing the mid degree of persistence of shocks like bad and good news, aiding in understanding the performance of these variables providing decision-making to managers, to act in long and short term.**

Keywords*-Box-Jenkins Models; SELIC Interest Rate; Exchange Rate; Volatility Models;*

1. Introduction

The volatile behaviour of certain economic variables has become an ever-present issue in the negotiations and prices of assets in interest and foreign exchange activities. The existence of volatility is due to changes in certain variables regarded to cause and/or effect with the variable under study. For example, in the Brazilian economic, context variable may be influenced by endogenous variables, such as economic policy adopted, domestic interest rate, among others. Besides the influence of internal variables, the same variable may also undergo changes due to exogenous variables such as the variability in the international price of a certain commodity, changes in international interest rates or even change in the volume of international capital flows.

By analyzing the volatility, it is noticed the relevance of studying the interest rate and exchange rate, knowing that both are strongly correlated with other variables in the macroeconomic sphere. According to Mankiw (2011), the interest rate has a significant role in driving the economy by influencing the intention of economic agents (households, firms and government). In contrast, variations in the exchange rate affect exports and imports, then modifying the applications in corporate investment besides modifying the trade balance.

Thus, under the perspective of the company, the behaviour of interest rates influences the price of the tangible and intangible assets, which are formed by corporate investment by transferring the cost of products. Considering Omar (2008), the interest rate also influences the exchange rate, which affects the price of durable goods, such as acquisition of machinery and equipment imports, reflecting the macroeconomic relationships such as inflation, unemployment, the rate capital flows and levels of external and domestic debt.

According to Melo (2010), there must be compatibility between monetary, fiscal, exchange rate policy and innovation policy (explicit) so that there is a favourable investment in innovation. Thus, entrepreneurs and government segments, in various spheres, can make their investment decisions based on the prevailing economic scenario.

Therefore, this study aims to analyze the behaviour of the rate of Settlement Depository System (Selic, in Portuguese), from January 1974 until June 2012 and the exchange rate from January 1980 to May 2012, through volatility models, in view of the relevance of these ones in the Brazilian economy.

This article is organized as follows: in section 2, the methodological aspects are described by highlighting the time series as well as modelling and demonstrating the applicability of such models; in Section 3, it is exposed the analysis and the discussion of results; and finally, Section 4 presents the final considerations.

2. Methodological Procedures

This research uses the time series of 'Selic' Interest Rate and the Exchange Rate, obtained at the website of Institute of Applied Economic Research (IPEA). 'Selic' consists of 462 monthly observations and the Exchange Rate with 389 observations. The methodological aspects are described below:

2.1. Analysis of the stationary series level

There is stability in time series by a visual inspection. Initially from a graphical analysis our analysis could confirm this stability of the time series. In order to go beyond, the unit root tests - through the Augmented Dickey Fuller (ADF)[1] and Kwiatkowski, Phillips, Schmidt and Shin (KPSS)[2] tests - were estimated. Next, the existence of autocorrelation in the series through Ljung-Box test was investigated. If this feature is present in the series, the modelling stage is begun by using the generic models 'Autoregressive Integrated Moving Average' - ARIMA, which is based on the theory that the behaviour of the variable is shown by the past information (Box and Jenkins, 1970).

Models ARIMA (p, d, q) are generic and there are other variations that are particular cases such as the AR (p) model showing that the value of Z_t in period t is explained by a proportion of its value in the previous period, or MA (q) where Z_t is a function of the sum of past errors, or may have a mixed form, a combination of features and autoregressive moving averages ARMA (p, q) in this study when the series is classified as stationary, to be represented by Equation 1.

$$\phi(B)Z_t = \theta(B)a_t \quad (1)$$

If the data set is stationary, the value of d will be automatically zero, i.e., d = 0. Otherwise, if the data set is non-stationary, it is required to use one or two differences to stabilize the variable, i.e., d = 1 or d = 2. Generally, ARIMA (p, d, q) model is represented by Equation 2.

$$\phi(B)\Delta^d Z_t = \theta(B)a_t \quad (2)$$

Where B is the lag operator, d is the integration order of the series, φ is the autoregressive term of order p and θ represents the parameter of moving averages of order q, a_t is the model residue with zero mean, constant and independent variance called white noise (Moretin, 2008).

The use of time series analysis consists in carrying out this method in three general stages: identification, estimation and diagnostic tests, subsequently performing the prediction if the research interest.

After finding several models that represent the series studied, these models are called competing models and penalty criteria are used in order to help choose the best model, namely: the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which use the maximized value of the likelihood function for the estimated model (L), number of parameters (n) and sample size (T) (Souza *et al*, 2012).

$$AIC = -2\ln(L) + 2n \quad (3)$$
$$BIC = -2\ln(L) + n\ln(T) \quad (4)$$

Considering the waste of competing models with characteristics of white noise, it becomes feasible to select the most suitable one to represent the series investigated in terms of the number of used parameters, which describe the model generating process, and it is useful for performing forecasts in future periods. At this stage of research, it is noted that ARIMA models are useful for describing the behaviour of the series in level.

[1] See Dickey and Fuller (1979).
[2] See Kwiatkowski *et al* (1992).

However, there is another investigation that should be conducted in order to describe the behaviour of the conditional variance, using the residues originating from ARIMA model described in this step.

2.2. Analysis of conditional variance

In some cases, even if the model of a time series presents residues which have those characteristics of white noise, there may still be some kind of dependence in the series that can be revealed when its quadratic residues are analyzed. This stylized fact is called the conditional variance. Considering the test for quadratic residual autocorrelation we estimated the ARCH-LM test. This test is used on the squared residuals of ARIMA model chosen in the previous step. When it is assumed the existence of heteroscedasticity, we seek to describe this variance, not constant over time, by means of nonlinear Autoregressive Conditional heteroscedasticity models - ARCH. This unconditional variance, after being modelled, assists in the interpretation of the volatility of the series, revealing features such as persistence as well as small and large periods of turbulence in the series - and volatility clustering help determine a measure of risk, since periods of high volatility represent periods of higher risk when assessing the stock market. But, in the macroeconomic context, large fluctuations allow to identify the stages of an economic crisis, as a crisis in the monetary, fiscal, exchange rate, etc.

The effect of non-constant variance is revealed by ARCH (p) models proposed by Engle (1982). They are very helpful in evaluating the behaviour of risk and return in financial markets. The conditional variance is expressed as a distributed lag of past squared errors, as in Equation 5.

$$a_t = \sqrt{\sigma_t^2}\varepsilon_t \tag{5}$$

$$\sigma_t^2 = \omega + \sum \alpha_i \,.\, \varepsilon_{t-i}^2 = \omega + \alpha(B)\varepsilon_t^2 \tag{6}$$

Where ω corresponds to the constant of this model and a_i represents the autoregressive component of past squared errors.

In these conditions this model can be well defined. The conditional variance must be positive, so the parameters must satisfy the following assumptions: $\Omega > 0$ and $\alpha_i > 0$. A disadvantage of ARCH models is that sometimes it is necessary to use a large number of lags *p* in the model to capture all effects of series which implies a high number of parameters and the violation of the principle of parsimony.

In order to overcome this difficulty shown by ARCH models, Bollerslev (1986) proposed a model called Generalized Autoregressive Conditional heteroscedasticity (GARCH) where the author included, in the ARCH model, the variance of the last series. Thus, it is possible to obtain a more parsimonious model and without the problems of estimating ARCH model, as shown in equation 8 model:

$$a_t = \sqrt{\sigma_t^2}\varepsilon_t \tag{7}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \,.\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \,.\, \sigma_{t-j}^2 \tag{8}$$

Being written again as:

$$\sigma_t^2 = \omega + \alpha(B)\varepsilon_t^2 + \beta(B)\sigma_t^2 \tag{9}$$

Where $\omega > 0$, e $\beta \geq 0$ ensuring that $a_t \geq 0$.

With the estimation of volatility models, it is possible to determine the dependence of the series variability and its past squared errors in the case of ARCH models, and can also determine the persistence of the series that is usually revealed by GARCH models (p, q), with the sum of parameters (α + β), where closer to 1, more persistent will be the effect of the non-constant variance, that is, the effect will be prolonged, taking a specified period to return to its usual level of variability.

Subsequently, Nelson (1991) proposed an extension of GARCH model, the Exponential GARCH (EGARCH), which captures the effects of random asymmetric shocks series. Since this kind of shocks have greater negative impact on volatility than positive (Tsay, 2005), the EGARCH model can show if the size effect of international oil prices variations or expansionary or restrictive monetary policies influence proportionally the volatility.

$$\varepsilon_t = \sqrt{\sigma_t^2}\varepsilon_t \tag{10}$$

$$ln\sigma_t^2 = \omega + \sum_{j-1}^{p} \beta_j \, ln\sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} - E\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \tag{11}$$

Where ε_t are *i.i.d.* $\sim \mathcal{N}(0, 1)$.

The logarithmic specification in EGARCH model is intended to prevent the conditional variance becomes negative providing that some model parameters can be negative. Moreover, in this model, the parameter γ captures the asymmetric shocks experienced in the series. These shocks can be negative or positive, and generally they produce a distinct impact on the volatility of the series.

In the financial markets, it is observed that periods of falling prices are often followed by periods of high volatility, while in periods of rising prices the volatility is not as intense. This fact is called “leverage effect”; In general, positive and negative shocks tend to have different impacts on volatility

In the financial literature, it is noticed the effect of leverage, where the negative shocks are identified – they are also called *bad news* - have a greater impact on the volatility of financial assets than positive shocks called *good news* series. The identification of EGARCH models verifies the effect of leverage when the γ parameter is less than zero (γ <0).

Besides the EGARCH model, the asymmetries in volatility can be captured by another variant of GARCH, the TARCH model (Zakoian, 1994), where the model THARCH conditional variance (p,q) Threshold Autoregressive Conditional Heteroscedasticity can be defined by:

$$\varepsilon_t = \sqrt{\sigma_t^2}\varepsilon_t \qquad (12)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2 + \cdots + \sum_{j=1}^{s} \alpha_j \sigma_{t-j}^2 + \gamma \varepsilon_{t-i}^2 d_{t-i} \qquad (13)$$

$$\text{Com } d_t = \begin{cases} 1, & se\varepsilon_t < 0 \ (\text{"}Badnews\text{"}) \\ 0, & se\varepsilon_t > 0 \ (\text{Good news"}) \end{cases}$$

If γ = 0, there is no asymmetry in the conditional variance, that is, the shocks experienced by the series do not differ when they are positive or negative. Negative shocks (*bad news*), in the market, are represented by negative errors (ε_t <0) and can be characterized by an abrupt fall in the dollar price or by political instability, and have an impact of (α + γ) in the volatility of the series. The positive impact or *good news* are represented by positive errors (ε_t> 0), for example, an increase in demand for a product and have impact α. Of course, the determination of shock types depends on which set the researcher is analyzing and on the context in which this variable is inserted.

After modelling the volatility using ARCH models new competitors will be taken, among which we must choose the most suitable one. Finally, penalizing criteria AIC and BIC are used. They were previously described for choosing the best representative model for the series under study. Thus, we have the ARIMA-ARCH model, where the first model is relative to the level of the series and the second one is relative to the volatility of it.

Finally, it is understood that the models described above, estimate the average or the mean and variance of the process together, accurately capturing the generating process of the series as well as the stochastic volatility. The use of this methodology provides the behaviour analysis of the time series modelling of checking whether a process average is sufficient, or whether it should still be taken into account to model the volatility of the series to obtain better results.

3. Results

Initially, it was carried out a visual inspection of the series, by means of graphs of sequences of interest rate (TXJ) from January 1974 to February 2014 and the exchange rate (TXC) from January 1980 to February 2014, shown in Figure 1 and 2, respectively. The series of interest rate shows an upward trend from 1974 to 1985 and, after this period the series presents an unstable period that stabilizes in mid-1996 after the establishment of the Real Plan, which allowed the balance in the Brazilian economy. The instability in the series, which may represent a volatile behaviour in the period beginning in the 80s and even the mid-90s, is justified by the Brazilian economical instability revealed by high interest rates and high levels of inflation.

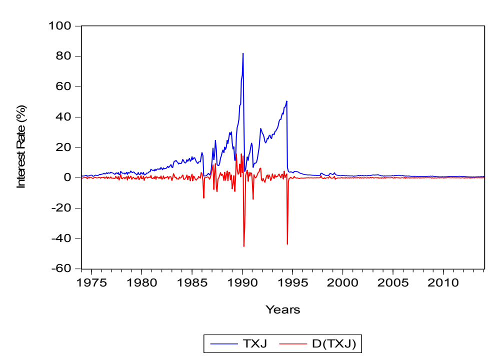

Figure 1. Evolution of SELIC interest rate and the series in first difference.

Source: IPEADATA.

Caption: TXJ = series in the level of interest rates; D (TXJ) = differentiated series (once) interest rate.

Figure 2 shows the graph of the exchange rate series and also shows that the series has a level shift where there is some variability in the examined period. Notice that with this, the level change starts from the year 1999.

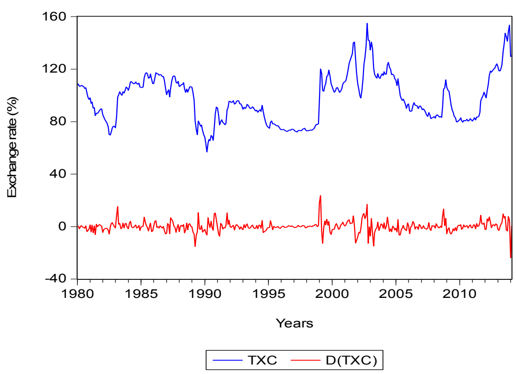

Figure 2. Evolution of the exchange rate series in level and the first difference in the series. Source: IPEADATA.
Caption: TXC = exchange rate; D (TXC) = differentiated series (once) of the exchange rate.

Besides the graphical inspection of the series, it was used the autocorrelation function (CAF) and the partial autocorrelation function (PACF), where the correlograms showed that the autocorrelation coefficients decrease slowly as the number of lags increases, showing that there is a strong dependence on the data, besides indicating the non-stationary condition of the series. To corroborate this statement of non-stationary status, the tests ADF and KPSS were applied, which indicate that the level series is not stationary for ADF having a p-value <0.05 and KPSS p-value> 0.05.

After checking through the tests ADF and KPSS that the series become stationary in first difference, we started the modelling process where we seek a model that could describe with the lowest possible error, the series behaviour (interest rate and exchange rate). To do so, several competing models were estimated, the selection was based on AIC and BIC criteria, being ARIMA (1,1,2) model chosen for the interest rate and ARIMA (0,1,1) model chosen for the series exchange rate. These models are for the first stage of the modelling performed in this study, that is, at first it was performed the modelling for the series level.

Then, it was analyzed the residues of these two chosen models - ARIMA (1,1,2) and ARIMA (0,1,1), which were characterized as white noise. The result of Jarque-Bera's test for the residuals of the first model (relating to interest rate) showed that the waste do not have a Normal distribution with p-value <0.0001 and the value of kurtosis > 3, showing an indication of heavy tails. The same result was found for the model of the exchange rate, where Jarque-Bera's test revealed a p value <0.0001 and a value of kurtosis greater than 3. Along with these statistics shown, there is strong evidence of the presence of volatility in the series. To confirm this residual volatility effect arising from ARIMA models, the ARCH-LM test was used and was significant by rejecting the null hypothesis and indicating the presence of conditional heteroscedasticity in the squared residuals of the model ARIMA (1,1, 2), that represents the interest rate Selic and of ARIMA (0,1,1) model, that represents the exchange rate. Therefore, it was necessary to model the existing volatility in the series in accordance with the results presented in Table 1 and their competing models.

After determining the most appropriate models for the variable interest rates and exchange rate models, ARIMA (1,1,1) - EGARCH (3,1,1) and ARIMA (0,1,1) EGARCH (1,1,1), were respectively found. ARCH test-LM was carried out in the residues modelling verifying that they do not possess heteroscedasticity and, by Box-Ljung test it was found that they are not auto-correlated besides having an average close to zero and attending the assumption of owning residues with characteristics of white noise.

When analyzing the competing models for the interest rate Selic shown in Table 2, it was found significance for all the estimated parameters and the confirmation that $\gamma \neq 0$, indicating the presence of asymmetry in the shocks of information. It was observed that in ARIMA (1,1,1) - EGARCH (3,1,1) model chosen, there is no leverage effect once $\gamma > 0$ for EGARCH models. In other words, it appears that there is an asymmetry in shocks, but there is no greater impact of negative shocks than of positive shocks in the volatility of the series.

The persistence of shocks in volatility in the chosen ARIMA (1,1,1) - EGARCH (3,1,1) model to the interest rate is captured by β where the parameter value is equal to 0.9976 being very high value indicating that shocks: *bad news* and *good news* tend to take a long time to resume their trajectory mean volatility of the period.

Table 1. Competing models for the interest rate Selic series and rates and white noise residues.

SELIC exchange rate			
	ARIMA(1,1,1) EGARCH (3,1,1)	**ARIMA(1,1,1) EGARCH (1,1,1)**	**ARIMA(1,1,2) TARCH (4,1,1)**
ϕ_1	0,4507	-0,9796	-0,4716
	(0,00001)	(0,00001)	(0,00001)
θ_1	-0,5924	0,9855	0,2253
	(0,00001)	(0,00001)	(0,0001)
θ_2	-	-	-0,4279
			(0,00001)
ω	-0,0530	-0,0992	0,0185
	(0,00001)	(0,00001)	(0,00001)
α_1	0,1239	0,0863	0,8005
	(0,0087)	(0,00001)	(0,00001)
α_2	0,2904	-	-0,4769
	(0,0022)		(0,00001)
α_3	- 0,3790	-	-0,1418
	(0,00001)		(0,0071)
α_4	-	-	0,5375
			(0,00001)
γ_1	0,3067	0,4095	-0,7698
	(0,00001)	(0,00001)	(0,00001)
β_1	0,9976	0,9980	0,2473
	(0,00001)	(0,00001)	(0,00001)
AIC	**19.210**	**19.470**	**21.684**
BIC	**19.906**	**19.991**	**22.553**
Exchange rate			
	ARIMA(0,1,1) EGARCH (1,1,1)	**ARIMA(1,1,0) EGARCH (1,1,1)**	**ARIMA(0,1,1) TARCH (1,1,1)**
θ_1	0,2960	0,2484	0,3031
	(0,00001)	(0,00001)	(0,00001)
ω	0,2227	0,2287	30.611
	(0,0001)	(0,00001)	(0,00001)
α_1	0,5293	0,5078	0,5846
	(0,00001)	(0,00001)	(0,00001)
γ_1	0,1564	0,1577	0,3277
	(0,00001)	(0,00001)	(0,0064)
β_1	0,7626	0,7673	0,4460
	(0,00001)	(0,00001)	(0,00001)
AIC	**52.808**	**52.960**	**52.977**
BIC	**53.299**	**53.452**	**53.467**

Notes:

ϕ_1 = autoregressive parameter ARIMA model;
ω = constant of the nonlinear model
α_i = the squared errors of ARIMA model
γ_1 = effect of asymmetry of volatility shocks
θ_i = moving average of ARIMA model
β_1 = the last variance

To understand the volatility of the series Selic interest rate in the 80s and 90s, it is important to emphasize that the oil crises (the first one in 1973 and the second in 1979) coupled with the change in the monetary policy of the United States (1978-1982) reflected the impact of these new trends of the world's capitalism over Brazil, and the consequences of such changes were worsened by some domestic economic policies implemented in the period [14].

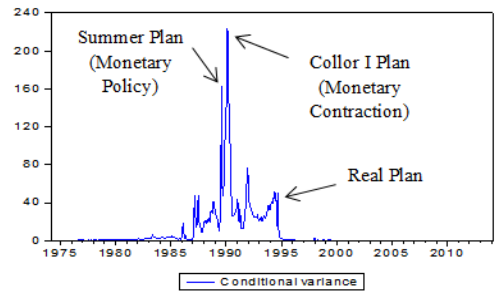

Figure 3. Graph of the Conditional Volatility of ARIMA (1,1,1) - EGARCH (3,1,1) model of the exchange rate.

After 'Cruzado' economical plan in mid-1986, still under José Carney's government, it started the so-called 'Summer' economical plan, in January 1989, which was short-lived. According Gremaud *et al.* [8], various factors such as the government's attempt to negotiate with the National Congress which aimed to increase the period of Sarney's government for five years concurrently with the elections of late 1989 (the campaign "Direct elections now"), among other political and economical aspects prevailing at the time mobilized fiscal and monetary control, causing a rise in inflation in 1989 and so, striding to hyperinflation, revealed by the volatility model.

In this context, Sarney's government was characterized by lack of public accounts, increases of operating deficits and growth in domestic borrowing. These characteristics led to the adoption of a restrictive monetary policy which aimed the support of high real interest rates which prevented the escape of dollars and real assets. Therefore, according to Cardoso (1991), the presence of high external debt, together with high interest rates, led to an increase in the inflation rate thereafter.

Thus, it is noticed in the volatility of the interest rate Selic series that the highest peak rate comes from the Brazilian hyperinflation that began in the last months of the summer in 1989 and followed up in mid-1990 when Brazilian inflation reached exceed 80% per month, demonstrating in mid-1993 that the economic plans adopted during Collar's government also failed like his predecessors. It can be seen in Figure 3.

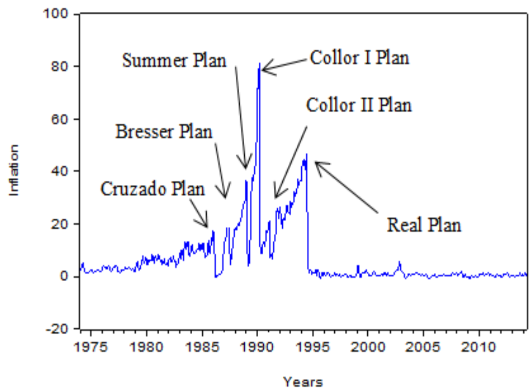

Figure 4. Evolution of Brazilian inflation - IGP-DI - (% per month).

By analyzing the behaviour of the interest rate Selic we note that Brazilian inflation has the same trajectory over time, showing strong variation of inflation and interest rate Selic in the 80s and 90s, stabilizing after that period. Thus, it confirms the strong relationship between the interest rate Selic and inflation, showing that both have the same behaviour over time as reported by Mankiw (2011).

For the exchange rate, ARIMA (0,1,1) EGARCH (1,1,1**)** model showed the best fit and therefore was a significant parameter. We verified the existence of asymmetry in the series and the γ parameter shows a significant value (γ ≠ 0) confirming the asymmetry in shocks of information. According to Ferreira, Menezes and Mendes (2007), it is noticed that, in the estimated model, it cannot be identified the lever effect, since γ> 0 in EGARCH models used. In summary the estimation showed that there is asymmetric information, where positive and negative shocks have different impact on volatility, but it is not seen the presence of the leverage effect.

As pointed Bueno (2008), the persistence of shocks in volatility of the chosen model ARIMA (0,1,1) - EGARCH (1,1,1) is captured by the parameter β equal to 0.7626 and this is an average value, demonstrating that positive and negative shocks – *bad news* and *good news* – in the volatility of the exchange rate series, tend not to take a long time to resume their trajectories in the process mean.

In Figure 5 it is exposed the conditional volatility of the exchange rate and it appears that the highest volatility peak occurs in 1999, when there was a change in the exchange rate regime in Brazil. On this date, it was adopted the floating exchange rate regime and the exchange rate went to oscillate exclusively depending on the supply and the demand in the market. It is also observed in Figure 5, the volatility of the series clearly shows that after the change of exchange rate regime in 1999, there is a stabilization of the exchange rate variability, because it returns to the previous level and fluctuates around the mean zero, showing that the change of exchange rate regime was effective for that period.

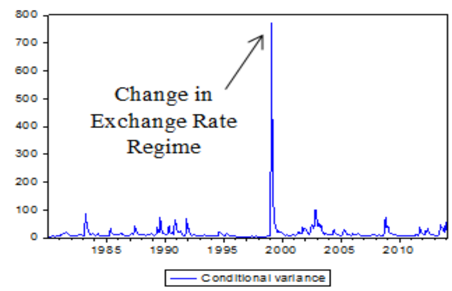

Figure 5. Graphic of the Conditional Volatility of model ARIMA (0,1,1) – EGARCH (1,1,1) of the exchange rate.

Thus, it appears that the use of joint ARIMA-ARCH model provided a better representation of the series in question, since both chosen models showed, in their graphical representations, their existing volatilities.

4. Final Considerations

In this study, it was carried out an empirical analysis of the volatility of the interest rate Selic and the exchange rate using joint modelling of the mean and the volatility of the process. The most suitable to the interest rate model was an ARIMA (1,1,1) - EGARCH (3,1,1) and the exchange rate of an ARIMA (0,1,1) - EGARCH (1,1,1), where we jointly modelled the process mean as well as the existing volatility in the residuals of ARIMA models.

The estimation of parameters confirmed the existence of asymmetric information for both models, where it appears that the shocks have different impacts on the volatility of the series. Moreover, the parameter that captures the persistence of shocks *bad news* and *good news* over the volatility of the interest rate series, because it has a value close to 'one', showed that the shocks experienced tend to reverberate for a long time. In contrast, for the exchange rate, this same parameter did not obtain a value close to unity 'one', showing that the persistence of shocks is mean.

Knowledge of the effect of persistence in volatility helps decision makers - businessmen and government - indicating that possible shocks arising from the internal policy adopted and/or due to international crises as occurred in the 80's and mid 90 tend to reverberate for a long time in the behaviour of interest rates. This does not occur in the behaviour of the exchange rate, where shocks do not have such a high persistence to interfere sharply in the oscillation of its performance over the period.

Thus, it is understood that internal or external economic crises affect the conduct of Brazilian monetary and fiscal policy and may alter the expectations of other economic agents.

Besides that, it is suggested for future studies the use of techniques for combining forecasting volatility in the models of ARCH family. Besides, it is also suggested the use of models that consider a forecast combination of the ARCH models, being able to capture effects that perhaps the time series analysis is unable to, suggest to expand the study using VAR-VEC models as Multiple Regression Analysis too.

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The Banking Crisis of 2007-2008, and Contemporary Responses

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***Abstract* - Until 2006, the financial system prospered and was stable, and Basel II rules were viewed as contributing to that stability. The financial crisis of 2007-2008 forced a change in those beliefs, as imbalances spread and risks materialized, affecting banks and other financial institutions, and impairing economic growth. We discuss the causes of the financial crisis, the response measures that were applied by governments, central banks and the changes in supervision and regulation that are being prepared under Basel III, to increase the resilience of banks, and to reduce the risks of future crisis.**

Keywords *– Banking Crisis; financial system; Basel II; supervision; regulation.*

1. The banking and financial system up to 2006

A strong banking system, robust and stable, with banks at the center of the credit process and as the main engine of the economy, is a fundamental condition for sustainable economic growth, in which the probability of occurrence of shocks on the real economy is minimized.

Until 2006, the dominant view was that financial systems were stable and resistant to adverse disturbances. The creditworthiness of counterparties to banks - firms and individuals - was considered high, and the macroeconomic and financial environment was favorable. Overall, the banking industry performed well, with increases in profitability and credit volumes registering low levels of impairment. The banks' total capital ratios remained comfortably above the regulatory minimum solvency ratio of 8%, even in the face of an increase in credit volumes.

The prevailing model of financial intermediation – originate-to-distribute model – allowed banks to distribute the credit risks they accepted to other financial agents and institutional investors (e.g. through securitization transactions) and thus release capital (e.g. own funds previously established to cover those risks), which, in turn, could be channeled into strengthening credit activity. The buyers of the credit risks originated by banks were pension funds, insurance companies, investment funds, hedge funds, who took this opportunity to diversify their portfolios.

The means available to ensure the security and stability of the financial systems provided comfort on the responsiveness to possible adverse events, including (i) guarantee funds deposits; (ii) protections for investors; (iii) regulators and supervisors; (iv) auditors and (v) the ability of central banks to grant loans. In this context, the implementation of the regulatory framework known as Basel II, represented a new form of supervision, with greater emphasis on the assessment and monitoring of risks, and allowed to predict the evolution of the risk management systems of banks in areas such as internal governance, technological solutions, and the widespread use of statistical tools in the estimation of risk in areas such as strategy, business and marketing. At the time, this was regarded as a significant step forward in the quality of supervision framework, and on the governance of banks, which was expected to become much more risk-aware and risk-oriented. Additionally, the continued prosperity and stability was proof that the system worked.

2. The financial crisis of 2007-2008

In 2007, the financial stability was significantly affected by a number of shocks originating in the North American subprime mortgage market, giving rise, for its scope and duration, to one of the most severe episodes of recent economic history (see a detailed account by Acharya *et al*, 2009). In the financial stability report of the European Central Bank, issued in 2007, we can find a survey of the main causes of the crisis, including the following.

At the macroeconomic level, the imbalances related to subprime credit affected the value of the portfolios of sovereign debt, particularly by way of inaccurate pricing of assets issued by certain countries (whose quality was lower than perceived), and a consequent contagion effect to third countries. Additionally, global imbalances resulting from persistently high deficits in the current accounts, led to capital flows from emerging countries to industrialized and rich economies, especially, the United States.

The low level of interest rates potentiated strong credit growth in most industrialized economies (e.g. real estate credit, consumption and for investment in assets with potentially higher returns than bank deposits), which led to a rise in prices of assets and the distortion of the macroeconomic framework in a broad set of countries. Clear signs of these distortions were the significant increases of real estate construction, the consumption of durable goods (especially cars) and the increasing size of the financial sector. Another problem was the fact that agents presumed that bank funding markets would remain liquid, in any circumstance.

At the microeconomic level, economic agents faced with various distortionary incentives. Individuals and firms maintained relationships with banks and investments made in firms (financial and non-financial) without getting properly informed about their financial situation. Managers of financial institutions contributed to the undercapitalization of institutions, via strong growth in financing by issuing bonds, with the aim of leveraging results, in order to increase the dividends payable to shareholders. Compensation schemes encouraged managers to make decisions neglecting the long term view, in favor of short-term objectives. Contracts for the transfer of credit risk were not structured in a way that ensured the right incentives, and that adequate resources were used, by the risk originating banks to continue to manage and control the underlying risks of credit activity, which potentiated the increase in defaults. The rating agencies attributed overly high ratings, in particular the bond issuers' entities, inadvertently contributing for the increase of systemic risk. The auditors developed their activity subject to a conflict of interests with their customers, because they are paid by those they audit.

Banks used inappropriate processes for monitoring and managing credit risk, using statistical tools based upon historical experience which, combined with a long period of relative stability, led to the perception that risk would be permanently low, thus under estimating it. This situation was compounded by the difficulty of estimating risk of new financial instruments to the extent that, with no historical data, these tools were not adequate to measure their risk.

Banks tended to accept the ratings of rating agencies at the expense of their own effort to evaluate the risks incurred. The positions taken by banks in complex financial products, as well as the actual perimeter of the potential exposure (e.g., via the designated structured investment vehicles) were, in general, opaque, hindering the identification and valuation of risks assumed. The largest international banks took excessive leverage and allowed the gradual erosion of the quality level of their capital base.

The matching of assets and liabilities showed a strong imbalance, with many banks holding insufficiently liquid assets. Additionally, some banks relied too much in wholesale funding markets in the very short term, in the incorrect assumption that it would always be possible to obtain liquidity in the markets.

Financial institutions found ways to move their business out of the regulatory perimeter, surpassing the limitations on leverage resulting from regulatory capital requirements, increasing their risk level, with the primary purpose of increasing profits. The result of these imbalances was the breakdown of the largest and most liquid financial markets in the world, triggering a severe contraction in real economy. The moment widely accepted as marking the loss of confidence in the financial system was the bankruptcy of the Lehman Brothers investment bank.

While the tools of risk assessment and pricing, and the management systems of financial institutions, were able to keep up with the innovations of financial products, the originate-to-distribute model contributed positively to the stability of the financial system. However, the financial crisis revealed weaknesses that were not supposed to exist in banks, insurance firms, investment and pension funds managing firms, and even governments, increasing the fear of a global system breakdown.

The originate-to-distribute model itself contributed to the amplification of the effects of the crisis, facilitating wider risk transfer. The risks that large banking groups had transferred to others, sometimes unexpectedly returned to the origin, through a link of successive financial instruments. Also, the holding of volatile assets (e.g. most vulnerable to abrupt changes in the conditions of the capital markets) contributed to a risk liquidity exposure greater than perceived.

Simultaneously, the financial turmoil affected the access to funding in wholesale markets, including money markets. The stress on liquidity gave rise to concerns about the credit quality of the portfolio and the adequacy of the capital levels. In turn, these concerns increased with the loss of investor confidence in the ability of certain financial institutions meeting their obligations.

In credit, the retail segment showed high vulnerability to adverse disturbances, given the high leveraging and the rising of short term interest rates. In firms, credit ratings downgrades became more frequent than upgrades, even though there was no increase in the frequency of defaults. Asset prices in credit markets began to adjust, by widening spreads in the renewal of transactions. However, in general, banks made no significant changes in their credit policies, maintaining a growth trend, and thus averting any immediate effect on the real economy.

3. Crisis response measures

The scenario of crisis and turmoil in financial markets, coupled with strong fears of propagation to the global economy, in third quarter of 2008, led to a concerted action of governing bodies, including governments and supervisory authorities, which adopted unprecedented intervention measures, in an attempt to prevent blocking of financial innovation and a reduction of the system efficiency.

The overall intervention by governments and central banks contributed to stop the negative effects of the interaction between the financial system and the economy, limiting the size of the economic downturn. This is critical, as systemic crises imply high costs, in terms of lost output, employment and fiscal costs (Reinhart and Rogoff, 2009). To this end, central banks implemented accommodative monetary policies, complemented with measures aimed at enabling the financial system to access liquidity and mitigating the disruptions in interbank money markets. Governments implemented fiscal and economic stimulus measures to support the financial system, with the goal of ensuring the stability of the latter and promoting the recovery of economic activity.

The main measures were: (i) reduction of interest rates to near zero (monetary policy); (ii) expansion of the balance sheets of central banks; (iii) government aid packages; (iv) fiscal stimulus on aggregate demand; (v) support by the central bank to financing needs of banks (providing liquidity) and (vi) direct support to the governments of credit to firms and households (e.g., in the form of guarantees to banks).

The commitment to avert the crisis, demonstrated by the implementation of successive measures, coupled with direct government support, calmed markets and prevented the collapse of the system, and several countries reached a more stable situation, by 2009, which continued in 2010.

4. Responses at the regulatory level

Prior to the beginning of the financial crisis, Basel II was seen as an important tool for strengthening risk management and prudential supervision, which would be conducted based on the perceived risk. Presumably, the conditions would be met to ensure that the banking systems in general and banks in particular, maintained a level of sustainable and adequate capital against the risk held.

However, the triggering and worsening of the crisis exposed a number of vulnerabilities and weaknesses in the international financial system and its regulation, uncovering a set of behaviors of agents that resulted from a misalignment of incentives. Consequently, and despite the fact that the Basel II regulatory framework includes stress testing, and rules that should ensure that banks can assess the potential losses they may incur from unlikely but plausible scenarios, a general consensus on the need to improve some elements of Basel II emerged (Blinder, 2010 and Moosa, 2010).

While in Basel I and II, the main focus was on the solvency capital, Basel III gives more focus to the problems too much leverage and inadequate buffers, by requiring different levels of reserves for different forms of bank deposits. The guidelines of Basel I and II were not abandoned, but are complemented with new requirements, that aim to correct the problems and imbalances revealed by the financial crisis of 2007-2008.

Thus, the Capital Requirements Directive II and III were prepared for the purpose of reviewing and improving Basel II, and the development of a package of supplementary prudential measures, called Basel III, was initiated, focusing mainly on: (i) strengthening the quality of capital banks and their solvency ratios, (ii) reducing leverage in the financial system (iii) harmonization of liquidity requirements, both in the short and in the long run and (iv) the introduction of countercyclical macroprudential measures. Basel III will raise the minimum capital requirements, and banks will face higher capital charges for market risk, for exposures to off balance sheet vehicles and derivatives and for the credit risk of trading counterparties (see Chouinard and Paulin, 2014).

A new non risk based leverage ratio defined as tier 1 capital to total assets, with a maximum of 3%, will act as a safeguard against the modelling and measurement of risks, and will also constrain leverage to rise during economic booms, and subsequent reducing, during recessions. Two new liquidity standards will be introduced, assuring that banks have adequate liquidity sources over a 30 day period, and also that they use stable sources of funding over the long run. Additionally, Basel III introduces a countercyclical capital buffer with the aim of moderating the amplitude of credit cycles, and avoiding credit crunches to the real economy, during economic downturns. These revisions and new measures will be phased in over the period 2013-2019.

Additionally, a consensus emerged that supervision and regulation should be improved and more centralized, with more specific rules, promoting best practices in risk management and internal governance, and correcting the misaligned incentives. Basel III imposes that, among other measures all banks must conduct much more rigorous analysis of the risk inherent in certain securities such as complex debt packages, and that banks implement much more complete disclosures than before the crisis, including their exposure to off-balance sheet vehicles, how they are reported in the accounts, and how banks calculate their capital ratios under the new regulations.

Some professionals worry that the rules of Basel III are too stringent, and may have gone too far, and that there is a real danger that reform will limit the availability of credit and reduce economic activity. Allen et al. (2012) claim that the problem is not higher capital and liquidity requirements per se but rather the difficulties of ensuring a coordinated adaption to the new rules across the entire financial services industry. The supervisory authorities will have to work together, to ensure an harmonized implementation, while correcting and adapting the new rules, in case they do not perform as intended or if they do not promote the desired effects. But what the financial crisis of 2007-2008 showed us all, is that we do need different rules to promote financial stability, than those we had under Basel II.

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Modeling long memory in the EU stock market: Evidence from the STOXX 50 returns

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Abstract **- This paper examines the persistence behaviour of STOXX 50 returns. To this end, we estimated the GARCH, IGARCH and FIGARCH models based on a data set comprising the daily returns from January 5th, 1987 to December 27th, 2013. The results show that the long-memory in the volatility returns constitutes an intrinsic and empirically significant characteristic of the data and are, therefore, in consonance with previous evidence on the subject. Moreover, our findings reveal that the FIGARCH is the best model to capture linear dependence in the conditional variance of the STOXX 50 returns as given by the information criteria.**

Keywords - *Stock long-memory; persistence; volatility; conditional variance; FIGARCH.*

1. Introduction

A major topic of research in Finance concerns the degree of persistence or long memory in stock returns. By long memory we mean a high degree of persistence in the time series. In particular, this concept can be generally expressed either in the time domain or in the frequency domain. In the time domain, long memory is characterized by a slow decay of the autocorrelation function of time series with larger sample data. This means that observations far from each other are still strongly correlated and decay at a slow rate. On the other hand, in the frequency domain the same information comes in the form of a spectrum. Thus, if the spectral density is unbounded at low frequencies, time series is said to exhibit a long memory process. Though both definitions are not equivalent they are related by the Hurst exponent – H (Beran, 1994), who was the first author to document this property in nature. Motivated by the desire to understand the persistence of the steam flow and therefore the design of reservoirs Hurst (1951) analyzed 900 geophysical time series and found significant long-term correlations among the fluctuation of the river Nile outflow. After his seminal work several other studies documented persistence in very distinct domains of Science, such as, Biology, Geophysics, Climatology and Economics, *inter alia*.

In addition, this phenomenon has also gathered much attention in Finance, which bases on an alternative approach built on the ARCH (Autoregressive Conditional Heteroskedasticity) type models to capture persistence in time series. In particular, the GARCH (General ARCH) process introduced by Bollerslev (1986) has become quite popular in modelling conditional dependence in financial volatility. However, though this constitutes an effective tool to capture volatility clustering it has revealed inappropriate to accommodate for persistence since it assumes that shocks decay at a fast exponential rate. Therefore, it is only suited to account for short-run effects. In an attempt to overcome this limitation Engle and Bolerslev (1986) developed the IGARCH (Integrated GARCH) framework, which allows infinite persistence. However, the infinite memory is a very unrealistic assumption, which motivated the need for an alternative approach. In the light of this, Baillie *et al.*

(1996) formulated the FIGARCH (Fractional Integrated) model, which characterizes an intermediate range of persistence. This is accomplished through the introduction of the fractional difference parameter *d*. Another advantage of this model is that it nets both GARCH, for $d = 0$, and IGARCH, for $d = 1$, processes as special cases.

Bearing on these models we investigate the degree of persistence of the EU stock market using the STOXX 50 index as a proxy. We use a data set comprising daily data from January 5th, 1987 to December 27th, 2013. The empirical results are, therefore, intended to broaden the available evidence to date and to characterize conditional dependence in the volatility process of the EU stock market. Moreover, we report estimates of the GARCH, IGARCH and FIGARCH parameters and use the information criteria to discriminate between models. Our aim is to find which model is more appropriate to characterize the dependence in the volatility process.

The rest of the paper proceeds as follows. Section 2 outlines the conditional volatility models, which is followed by a description and initial analysis of the data in Section 3. Section 4 presents the empirical results and, finally, Section 5 concludes the paper.

2. Model framework

2.1 GARCH model

Following Engle (1982) consider the time series y_t and the associated prediction error $\varepsilon_t = y_t - E_{t-1}\left[y_t\right]$, where $E_{t-1}\left[.\right]$ is the expectation of the conditional mean on the information set at time *t*-1. The standard GARCH(*p*,*q*) model introduced by Bollerslev (1986) is defined as:

$$\sigma_t^2 = \omega + \alpha\left(L\right)\varepsilon_t^2 + \beta\left(L\right)\sigma_t^2, \qquad (1)$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, L denotes the lag or backshift operator $\alpha\left(L\right) \equiv \alpha_1 L + \alpha_2 L^2 + ... + \alpha_q L^q$ and $\beta\left(L\right) \equiv \beta_1 L + \beta_2 L^2 + ... + \beta_p L^p$. Hence, according to the GARCH formulation the conditional variance is a function of (i) the past squared residuals and of (ii) the lagged values of the variance itself (Daly, 2008). In general, a GARCH(1,1) specification is sufficient to describe the vast majority of time series and rarely is any higher order model estimated. The great advantages of this model when compared to the seminal ARCH of Engle (1982) are two-fold: (i) it is more parsimonious and (ii) avoids overfitting. Consequently, the model is less prone to breach non-negativity constraints.

A common empirical finding in most applied work is the apparent persistence implied by the estimates for the conditional variance. This is manifested by the presence of an approximate unit root in the autoregressive polynomial, that is, $\alpha + \beta \approx 1$, meaning that shocks are infinitely persistent (Bollerslev *et al.*, 1992). As the GARCH formulation considers that shocks decay at a fast geometric rate this specification is not appropriate to describe long memory, being only suited to accommodate for short-memory phenomena.

2.2 IGARCH model

In order to overcome this limitation Engle and Bollerslev (1986) derived the IGARCH model, which captures *I*(1) type processes for the conditional variance as infinite persistence remains important for forecasts of all horizons. Assuming that $\upsilon_t \equiv \varepsilon_t^2 - \sigma_t^2$ the GARCH model can be re-written in the form of an ARMA(*m*,*p*) process

$$\Phi\left(L\right)\left(1-L\right)\varepsilon_t^2 = \omega + \left[1-\beta\left(L\right)\right]\upsilon_t, \qquad (2)$$

where $\Phi\left(L\right) = \left[1-\alpha\left(L\right)-\beta\left(L\right)\right]\left(1-L\right)^{-1}$ and all roots of $\Phi\left(L\right)$ and $\left[1-\beta\left(L\right)\right]$ lie outside the unit root circle.

However, despite its insight when compared to its predecessor this model is not fully satisfactory in describing long memory in the volatility process as shocks in the IGARCH methodology never die out.

2.3 FIGARCH model

In an attempt to describe the long memory process in a more realistic way Baillie *et al.* ([1] introduced a new class of models called FIGARCH. In contrast to an *I*(0) time series in which shocks die out at a fast geometric rate or an *I*(1) time series where there is no mean reversion, shocks to an *I*(*d*) time series with $0 < d < 1$ decay at a very slow hyperbolic rate.

The FIGARCH(*p*,*d*,*q*) model can be obtained by replacing the difference operator in Eq. (2) with a fractional differencing operator $(1-L)^d$ as in the following expression:

$$\Phi(L)(1-L)^d \varepsilon_t^2 = \omega + \left[1-\beta(L)\right]\upsilon_t. \quad (3)$$

Rearranging the terms in Eq. (3), one can write the FIGARCH model as follows:

$$\left[1-\beta(L)\right]\varepsilon_t^2 = \omega + \left[1-\beta(L)-\Phi(L)(1-L)^d\right]\varepsilon_t^2. \quad (4)$$

The conditional variance of ε_t^2 is obtained by:

$$\sigma_t^2 = \frac{\omega}{\left[1-\beta(L)\right]} + \left[1-\frac{\Phi(L)}{\left[1-\beta(L)\right]}(1-L)^d\right]\varepsilon_t^2, \quad (5)$$

which corresponds to

$$\sigma_t^2 = \frac{\omega}{\left[1-\beta(L)\right]} + \lambda(L)\varepsilon_t^2, \quad (6)$$

where $\lambda(L) = \lambda_1 L + \lambda_2 L^2 \ldots$

The FIGARCH metodology provides greater flexibility for modeling the conditional variance, because it accommodates the covariance stationary GARCH model when $d = 0$ and the IGARCH model when $d = 1$, as special cases. For the FIGARCH model the persistence of shocks to the conditional variance or the degree of long memory is measured by the fractional differencing parameter d. Thus, the attraction of this methodology is that for $0 < d < 1$, it is sufficiently flexible to allow for an intermediate range of long memory. It is worthy to note that the parameters of the FIGARCH model can be estimated by an approximate quasi-maximum likelihood estimation technique (Bollerslev and Wooldridge, 1992).

3. Data and some preliminary statistical results

The data employed in this study consist of the daily closing prices for the STOXX 50 during the period from January 5th, 1987 to December 27th, 2013, which totals 7040 observations. STOXX 50 index was designed to provide a Blue-chip representation of supersector leaders in the Eurozone and covers 50 stocks from 12 Eurozone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. Because the STOXX 50 is considered to be a proxy of the overall Eurozone stock market, it is frequently used as the underlying index for several derivative financial instruments such as options, futures, index funds and structured products. Figure 1 plots the STOXX 50 daily returns'.

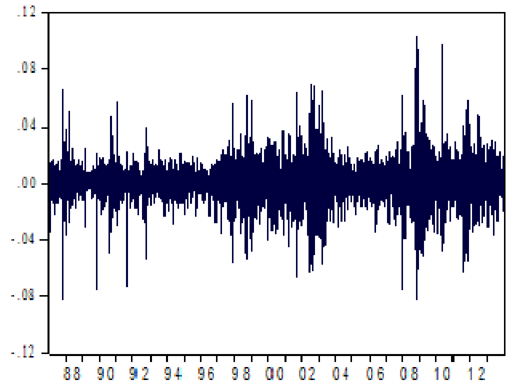

Figure 1. STOXX 50 daily returns'

More specifically, we define the STOXX 50 daily returns' as

$$R_t = \ln P_t - \ln P_{t-1}. \quad (7)$$

where R_t denotes the index returns at time t, and P_t and P_{t-1}, prices at time t and t-1, respectively. The data were collected from Datastream database.

Preliminary analysis for the STOXX 50 returns over the period under consideration is displayed in Table 1. Starting with the descriptive statistics we find that the average daily returns are positive and very small when compared to the standard deviation. The series is also characterized by negative skewness and high levels of positive kustosis, indicative of a heavier tailed distribution than the Normal. Jarque-Bera (J-B) test further confirms departure from normality, which can be graphically observed by looking at the plot of the histogram (Fig. 2). Accordingly, these results encourage the adoption of an alternative distribution, which embodies these features of the data, such as, the GED (Generalized Error Distribution) distribution.

Table 1. Preliminary analysis of STOXX 50 daily returns

Panel A. Summary statistics

Mean	Std. Dev.	Skewness	Kurtosis	J-B	$Q(10)$	BG(10)
0.000176	0.013272	-0.15006	9.031538	10696.21**	56.159**	5.549556**

Panel B. Heteroskedasticity tests

ARCH-LM	$Q^2(10)$
155.5133**	3792.4**

Panel C. Unit root tests

	ADF	KPSS
intercept	-40.0337**	0.178982
trend + intercept	-40.04168**	0.086268

Notes: 1. Denotes significantly at the 1% level. 2. J-B represents the statistics of the Jarque and Bera (1987)'s normal distribution test. 3. $Q(10)$ denotes the Ljiung-Box Q test for the 10th order serial correlation for the null hypothesis of no autocorrelation. 4. BG reveals the Breusch-Godfrey test for the null hypothesis of no serial correlation up to 10 lags. 5. ARCH-LM refers to the ARCH test for the null of no autoregressive conditional heteroskedasticity up to 10 lags. 6. $Q^2(10)$ is the Ljiung-Box Q test for serial correlation in the squared standardized residuals with 10 lags, which is used to check for ARCH effects. 7. ADF defines the Augmented Dickey and Fuller (1979) test for the null of non-stationarity. Critical values: -3.43 (1%) and -2.86 (5%) for constant and -3.96 (1%) and -3.41 (5%) for constant and linear trend. 8. KPSS indicates the Kwiatkowski, Phillips, Schmidt and Shin (1992) test for the null of stationarity. Critical values: 0.739 (1%) and 0.463 (5%) for constant and 0.216 (1%) and 0.146 (5%) for constant and linear trend.

Moreover, the Ljiung-Box Q-statistics ($Q(10)$) and the Breusch-Godfrey statistics both reveal serial correlation. In addition, the results for the ARCH-LM and $Q^2(10)$ tests are highly significant, thus unveiling ARCH effects.

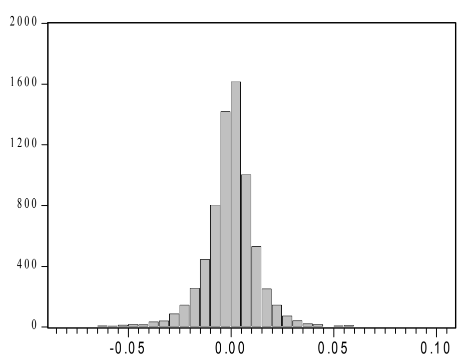

Figure 2. Histogram of the daily returns of the STOXX 50

Turning to the unit root tests (Table 1 – Panel C), an analysis of the ADF and KPSS statistics unfolds that the return series is stationary. In fact, the ADF test rejects the null hypothesis of non-stationarity at the 1% significance level, while for the KPSS the null of stationarity in not rejected. Both tests were estimated considering a constant and a constant and a linear trend in the exogenous regressors.

4. Model estimates

In order to remove any serial correlation present in the data[1] we first fit an AR(p) model (Autoregressive model). In this context we chose an AR(5) specification to account for this feature of the data. Table 2 provides the residual analysis for this specification. Results show that the residuals are non-normally distributed as the Jarque-Bera test is rejected at the 1% level. This is also implied by the negative skewness and excess kurtosis evidenced by the residual series. In addition, the Ljiung-Box and Breusch-Godfrey statistics both indicate no evidence of serial dependence, thus revealing that this specification is adequate in describing the linear dependence in the data. Nevertheless, residuals still exhibit conditional heteroskedasticity given that the ARCH-LM and the Ljiung-Box statistics of the squared residuals are all significant at the 1% level. Therefore, a specification that accounts for this property should be used to model the data.

Table 2. Residual's analysis for the fitted AR(p) model

Panel A. Summary statistics

Mean	Std. Dev.	Skewness	Kurtosis	J-B	$Q(10)$	BG(10)
-2.37E-20	0.013227	-0.247482	8.742039	9735.055**	7.5577	0.984831

Panel B. Heteroskedasticity tests

ARCH-LM	$Q^2(10)$
156.7961**	3825.3**

Notes: 1. Denotes significantly at the 1% level. 2. J-B represents the statistics of the Jarque and Bera (1987)'s normal distribution test. 3. $Q(10)$ denotes the Ljiung-Box Q test for the 10th order serial correlation for the null hypothesis of no autocorrelation. 4. BG reveals the Breusch-Godfrey test for the null hypothesis of no serial correlation up to 10 lags. 5. ARCH-LM refers to the ARCH test for the null of no autoregressive conditional heteroskedasticity up to 10 lags. 6. $Q^2(10)$ is the Ljiung-Box Q test for serial correlation in the squared standardized residuals with 10 lags, which is used to check for ARCH effects. 7. ADF defines the Augmented Dickey and Fuller (1979) test for the null of non-stationarity. Critical values: -3.43 (1%) and -2.86 (5%) for constant and -3.96 (1%) and -3.41 (5%) for constant and linear trend. 8. KPSS indicates the Kwiatkowski, Phillips, Schmidt and Shin (1992) test for the null of stationarity. Critical values: 0.739 (1%) and 0.463 (5%) for constant and 0.216 (1%) and 0.146 (5%) for constant and linear trend.

Given this, we start by fitting the standard GARCH(1,1). Subsequently, in order to account for persistence the IGARCH(1,1) and FIGARCH(1,d,1) specifications are also estimated. All parameters were estimated by quasi maximum likelihood estimation method in terms of the BFGS optimization algorithm using the econometric package of OxMetrics 5.00. Since the returns follow a distribution with thicker tails than the normal, as shown in Section 3, we assumed a GED distribution for estimation purposes. Model estimates and diagnostic tests are provided in Table 3. As one can observe, the parameters ω, α, β of the GARCH equation and the tail coefficient of the GED distribution are all positive and found to be highly significant. Further, there is also evidence of strong persistence in the return series, as $\alpha + \beta \approx 1$, which motivated the estimation of the IGARCH(1,1) and FIGARCH(1,d,1) models. As in the GARCH case, results for these specifications uncover positive and highly significant parameters at the 1% level. A fractional difference parameter of 0.46053 was found for the return series, which shows a moderate level of persistence.

A number of diagnostic tests were then performed in order to assess the adequacy of these models in describing the returns volatility. According to our results, the p-values of the Ljung-Box Q statistic test at lag 10 of the standardized residuals for all models fail to reject the null of no autocorrelation at the 1% significance level. Therefore, all models appear to be adequate in describing the linear dependence in the return series. In addition, for all the three models considered the ARCH-LM(10) test cannot reject the null hypothesis of no ARCH effects. This is corroborated by the Ljiung-Box statistics of the squared residuals, which is significant at the 1% level, thus unfolding that these specifications are sufficient to capture conditional heteroskedasticity in the conditional variance equation. Finally, there is still evidence of non-normality in the residual series as the Jarque-Bera test rejects the null of Gaussianity at the 1% level.

Having estimated these three specifications one question remains to be answered: which one is the best model to describe conditional dependence in the volatility process? In order to discriminate between models we employ the LL (log-likelihood), AIC (Akaike Information Criterion) and SIC (Schwarz Information Criterion) information criteria. According to Sin and White [13] the most appropriate model to describe the data is the one that maximizes the LL function and minimizes the SIC and AIC criteria. In our particular case, the model that fulfills these conditions is the FIGARCH(1,d,1) model. This is not surprising as the results obtained in the GARCH formulation also suggested persistence since the sum of α and β is very close to 1.

Table 3. GARCH(1,1), IGARCH(1,1) and FIGARCH (1,d,1) estimates

Parameter	GARCH (1,1)	IGARCH (1,1)	FIGARCH (1,d,1)
ω	0.019349**	0.014945**	1.579819**
	(0.0000)	(0.0001)	(0.0053)
d	---	---	0.46053**
	---	---	(0.0000)
α	0.096188**	0.104375**	0.121130**
	(0.0000)	(0.0000)	(0.0020)
β	0.894336	0.895625**	0.518799**
	(0.0000)	(0.0000)	(0.0000)
GED	1.31078	1.295030**	1.321006**
	(0.0000)	(0.0000)	(0.0000)
LL	22026.727	22023.625	22041.272
AIC	-6.255641	-6.255043	-6.259489
SIC	-6.245896	-6.246273	-6.24877
J-B	14696**	18727**	15000**
	(0.00000)	(0.00000)	(0.00000)
$Q(10)$	7.49615	7.64307	8.61503
	(0.1862771)	(0.1770350)	(0.1254403)
ARCH-LM	0.13182	0.13897	0.11751
	(0.9994)	(0.9992)	(0.9996)
$Q^2(10)$	1.32262	1.38635	1.18414
	(0.9952764)	(0.9944382)	(0.9967962)

Notes: 1. The p-values are included in parenthesis. 2. GED refers to the tail coefficient of the GED distribution. 3. LL refers to the log-likelihood value 4. SIC designates the Schwarz Information Criterion. 5. AIC denotes the Akaike Information Criterion. 6. ** Indicates the rejection of the null hypothesis at the 1% significance level. 7. J-B represents the statistics of the Jarque and Bera (1987)'s normal distribution test. 8. $Q(10)$ denotes the Ljiung-Box Q test for the 10th order serial correlation for the null hypothesis of no autocorrelation. 9. ARCH-LM refers to the ARCH test for the null of no autoregressive conditional heteroskedasticity up to 10 lags. 10. $Q^2(10)$ is the Ljiung-Box Q test for serial correlation in the squared standardized residuals with 10 lags, which is used to check for ARCH effects.

5. Conclusions

In order to examine the degree of persistence of the STOXX 50 daily returns' we estimated three different models of conditional volatility – GARCH, IGARCH and FIGARCH models. To this end, we collected data from January 5th, 1987 to December 27th, 2013.

Basically, we conducted our study in three steps: first, we provided a preliminary analysis on the data based on the descriptive statistics of the variable under consideration. Our results showed that the STOXX 50 returns did not follow a normal distribution. In addition, we demonstrated that though prices were non-stationary returns were stationary, thus enabling further analysis. Moreover, we also found serial correlation and conditional heteroskedasticity in the return series. Second, and in order to capture the autocorrelation we fitted an AR(5) model, which proved to be sufficient to remove any serial dependence in the series. Nonetheless, heteroskedasticity was still present in the returns. Finally, we estimated the GARCH, IGARCH and FIGARCH parameters and used the information criteria to discriminate between models. Our results showed a moderate level of persistence (d = 0.46053). Furthermore, the FIGARCH model was proven to be the best model to describe the data. Finally, residual tests also revealed absence of serial correlation and ARCH effects.

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PSI-20 Portfolio Efficiency Analysis with SFA

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***Abstract* - The determination of the study was to assess the technical efficiency of the individual companies and their respective groups of the Portuguese stock market. In order to achieve that were combined the input variables "market value and return" with exogenous variables such as "interest income," "depreciation," "cost of goods," "employees" and "net sales" in a Stochastic Frontier Analysis model. The technical efficiency of the PSI-20 enterprises index was estimated discovering the factors which assurance to efficiency variability, applying the SFA approach main improvement which lies in its potential to categorize between measurement error and systematic inefficiencies in the estimation process. The results revealed that the technical efficiency is higher for the enterprises in industry, construction and distribution economic sectors whereas the commercial banking sector has the lowest technical efficiency scores. The "employees" and "depreciation" variables are the elements that most enhance to the stock market inefficiency.**

Keywords *– Stochastic Frontier Analysis; Efficiency; Stock Markets; PSI-20*

1. Introduction

Financial researchers have long been interested to examine whether there is difference between factors influencing business and financial performance. Many studies have emphasized the need for the company´s to increase its competitiveness, and have suggested the use of performance measurement as a tool for continuous improvement. General measurement of a company's performance and subsequent feedback to its managers is vital for business transformation. Measurement also enables businesses to be compared with each other on the basis of standardized information, allowing best practices to be identified and applied more widely.

The general concept of efficiency refers to the difference between observed and optimal values of inputs, outputs, and input-output mixes. In literature, Decision Maker Units (DMUs) are production units (e.g. firms, regions, countries, etc.) which assumed to produce according to a common technology. Each DMU reach the frontier when produces the maximum possible output for a given set of inputs, if the analysis is output oriented. When the orientation is inverse (input oriented) the frontier is reached when the DMU maintain an expected output consuming the minimum of inputs available. Notwithstanding, the performance measurement concerns different notions of efficiency (e.g. revenue, technical, productive and allocative). Market failure occurs due to inefficiency in the allocation of goods and services. For this matter, the search for inefficiency is sometimes justified due to structural problems or market imperfections or even other factors, resulting in firms producing below their maximum attainable output. Efforts to measure how efficiently a firm produces outputs with its inputs have led to the development of a number of efficiency concepts, including scale efficiency, scope efficiency, economic efficiency, and technical efficiency. Whereas technical efficiency requires only input and output data, economic efficiency also requires price data. A substantial number of literature had documented two broad paradigms for measuring economic efficiency, one based on an essentially nonparametric, programming approach to analysis of observed outcomes, and one based on an econometric approach to estimation of theory based models of production, cost or profit. Following the latter paradigm, the Stochastic Frontier Analysis (SFA) of Aigner *et al* (1977) is in our days a very popular model for efficiency measurement purposes, being the Cobb-Douglas and the Translog the most frequently applied models in literature of econometric inefficiency estimation.

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The use of SFA in capital market studies is relatively new. Notwithstanding, an extensive survey of the underlying models, econometric techniques and empirical studies can be find in several papers. Among several others, Das and Kumbhakar (2012) focus their analysis in the stock market, proposing an alternative approach to empirically modelling financial constraints, using SFA to estimate a measure of financial constraint for each DMU of a panel of Indian manufacturing firms. Muradoglu and Sivaprasad (2013) explored the effect of leverage mimicking factor portfolios in order to explain the stock return variations. Several studies followed similar approaches to define the percentage that could be increased in the market value of an average DMU regarding the benchmark, considering the efficient use of all resources (e.g. Habib and Ljungqvist (2005); Pawlina and Renneboog (2005); Nguyen and Swanson (2009). In contrast to using market value frontier to measure efficiency, Amess and Girma (2009) use an empirical model to evaluate the effect of efficiency on the market value, applying a SFA approach to estimate TE involving revenue, number of employees and fixed assets.

2. Methodology

2.1 Dataset

Using the 20 companies of the PSI-20 index, between 01/01/1993 and 01/09/2013 obtained from Datastream database (Table 1), the stock Portuguese index market includes 7 categories of companies, namely: Banks, Industry, Media, Energy, Food & Allied Products, Construction and Communications (5, 3, 1, 4, 4, 1 and 2 companies, respectively). The panel data composition was set considering the individual company's return as a dependent variable. The market return was taken by preparing individual company's daily closing price by using which the return of individual company calculated as follows: Individual Market Return = $\ln(P_t) - \ln(P_{t-1})$ where P_t is the closing price at period t, and P_{t-1} is the closing price at period t-1 and ln is the natural log.

Table 1 - List of the Companies from PSI-20 Index

Group	Company
Industry	Altri SGPS
	Portucel
	Semapa
Construction	Mota Engil SGPS
Food and Allied Products	Jerónimo Martins
	Sonae Indústria SGPS
	Sonae.com
	Sonae SGPS
Media	Cofina
Comunications	Portugal Telecom SGPS
	Zon Optimus
Energy	EDP Renováveis
	EDP Energias de Portugal
	GALP Energia SGPS
	REN
Banks	Banco Comercial Português (BCP)
	Banco Espírito Santo (BES)
	Banco Português de Investimento (BPI)
	BANIF
	Espírito Santo Financial Group

2.2. Data analysis

Considering a stochastic frontier model (Battese and Coelli, 1995), where each DMU is denoted by i, the individual return is obtained by the following production function:

$$\ln(y_i) = x_i\beta + (v_i - u_i) \qquad (1)$$

and where; $i = 1, 2, \ldots, N$; y_i measures the individual return of the i^{th} company; x_i is a 1 x K vector corresponding to the inputs (Individual Market Return and Market Value); and β is a 1 x K vector of unknown scalar parameters to be estimated. In this model, the usual error term ε can be decomposed in two distinct terms v_i-u_i (1) for each DMU. The error term v_i is similar to that in traditional regression model, and likewise is assumed to be independently and identically distributed as $N(0, \sigma_v^2)$. This term captures random variation in output due to factors beyond control of the DMUs, such as measurement errors in dependent variables or explanatory variables eventually omitted. The error term u_i is a non-negative random variable, accounting for the existence of technical inefficiency in production being identically distributed as half-normal $u_i \sim |N(0,\sigma^2)|$. The subtraction of the non-negative random variable u_i, from the random error v_i, implies that the logarithm of the production is smaller than it would otherwise be if technical inefficiency did not exist (Battese and Coelli (1995). According to Battese and Coelli (1995), the inefficiency distribution parameter can also be specified as the inefficiency model: $u_i = \delta_0 + z_i\delta + \omega_i$ (2)

where; δ is a vector of parameters to be estimated, z_i is a vector of DMU specific effects (Interest Income;

Depreciation; Cost of Goods; Employees and Net Sales) that determine technical inefficiency and ω_i is distributed following N(0, σ_ω^2). All observations either lie on, or are beneath the stochastic production frontier and this is assured by $u_i \geq 0$ in Equation (2). The variance terms are parameterized by replacing σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{(\sigma_v^2+\sigma_u^2)}$ according Battese and Corra (1977) and Battese and Coelli (1995). With the value of γ ranged between 0 and 1, the equality to 1 indicates that all the deviation from the frontier are entirely due to technical inefficiency (Coelli, Rao and Battese, 1998) being the technical efficiency of each DMU expressed as follows:

$$TE_i = \frac{E(Y_i|u_i,X_i)}{E(Y_i|u_i=0,X_i)} = e^{-u_i} \tag{3}$$

The E is the expectation operator and thus the measure of technical efficiency is based on a conditional expectation given by Equation (3), considering that the value of $v_i - u_i$ evaluated at the maximum value of Y_i is conditional on $u_i = 0$ (Battese and Coelli, 1988).

The parameters of the stochastic frontier model (1) and the technical inefficiency model (2), were estimated using the FRONTIER version 4.1 software (Coelli, 1996). The statistical tests were performed with SPSS®.

3. Empirical Results

Initially it was estimated the parameters of the stochastic frontier model (1) and the inefficiency model (2). Table 2 reports the maximum-likelihood estimates of the parameters of the models, the corresponding standard errors, and the test statistics.

These estimates justify that the inclusion of the inefficiency effects is highly significant (at 1% level) in the analysis of market returns, as the estimate for the variance is closed to one (γ=0.975). From this it can being interpreted that 97.5% of random variation in stock returns is due to inefficiency. This can also be interpreted that the 97.5 percentage variation in output among the companies is due to the differences in technical efficiency.

It is evident from Table 2 that the estimates of σ (0.81) are significantly (at 1% level) different from zero indicating a good fit and correctness. Regarding the SFA model, the maximum-likelihood estimates of the coefficients of market return and market value are found to be significant at 1% level. These results indicate that the input variables significantly affect the amount of return in the individual companies listed in the PSI-20.

The market return shows significant relationship with the stock returns which means that if the overall market rises, then the return of individual companies will increase, and if the overall market falls, then the return of individual companies will decrease. The other input variable, namely the market value also shows significant relationship with the stock returns which means that if the market value of individual company shows upper trend, then the return of that company will increase, whereas if it shows lower trend, then the return of that company will decrease.

Table 2 - Maximum-Likelihood Estimates of the Stochastic Frontier Production Function

Variable	Coef.		Std. Error
Stochastic frontier model			
constant	-1.206	**	0.035
ln(market return)	1.214	**	0.033
ln(market value)	0.007	**	0.002
Inefficiency model			
constant	-2.250	**	0.051
Interest Income	0.003	*	0.002
Depreciation	0.021	**	0.005
Cost of Goods	0.007	**	0.002
Employees	1.451	**	0.052
Net Sales	-0.006	**	0.002
sigma-squared	0.810	**	0.001
gamma	0.975	**	0.001

** significant at 1%; * significant at 5%.

These results support previous results (e.g. Hasan *et al,* 2012) in a sense that positive relationships between those input variables are common. Concerning the inefficiency model results from Table 2, it is possible to conclude that "Interest Income", "Depreciation", "Cost of Goods" and "Number of Employees" are in fact, factors that contribute to the companies' inefficiency. Only the "Net Sales" do the opposite. Despite all of the factors being statistically significant, the "number of Employees" is the one that most affect the inefficiency with a coefficient of 1.451. Being a positive impact means that bigger companies tend to be less efficient whereas companies with less employees tend to be more efficient. A comparable interpretation can be done with the remaining coefficients. In the case of the "Net Sales", the reading of the results should be inverse, meaning that more sales have less impact in the inefficiency, in fact those sales contribute to the company's efficiency.

4. Discussion

This paper studies the technical efficiency of Portuguese enterprises of the PSI-20 index stock market over the period 1993–2013 using stochastic frontier analysis. The period examined in the study is extensive, covering the changing background faced by the major enterprises, financial crises, and many enterprises restructuring processes. During this time window, it was celebrated twenty years of existence of the Maastricht Treaty. In this context, it is reasonable to ask about the current status of the index stock market returns Portuguese efficiency performance. Taking these dynamics into contemplation, this study offers new evidence on the time series properties of the efficiency of the major Portuguese enterprises. Consistent with earlier studies, the results show substantial inefficiencies in the Portuguese enterprises. The estimated model concluded that 97.5% of random variation in stock returns is due to inefficiency.

The number of employees is the factor that most affect the inefficiency means that bigger companies tend to be less efficient. Focusing the analysis by year, the paper achieved the conclusion that the first year of the sample (1993) stayed below the averaged efficiency. This fact was certainly due to the conciliation of this year was the year of the PSI-20 creation.

The model results showed that the three greatest technical efficient groups were Industry, Construction and Food and allied products. The authors believe that the results of this study are very interesting for several players both from academic field and investors and regulatory authorities.

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Network Models in Economics and Finance – A Book Review

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Abstract – **Through this work the book "Network Models in Economics and Finance", 978-3-319-09683-4, vol. 100 in Springer Series "Springer Optimization and Its Applications" is reviewed. Valery A. Kalyagin, Panos M. Pardalos, Themistocles M. Rassias, Editors of this book describe briefly its content as a book that:**
-Contains new tools for financial data mining and discusses the uncertainty of the network market analysis,
-Provides network analysis to the financial crises,
-Includes methods of network analysis applied to corporate governance and investment tools.
The keywords and the related subjects presented below, also supplied by the Editors, give a complete idea about the broad range of the subjects dealt with in this book and also on the analytical tools used and described. The whole book is written in a very readable English, but also with style. The subjects are presented in a very clear way, with no loss of scientific rigor. So this is an important book not only for the evident enormous importance of the theme but also because its accessibility to the readers allows a great dissemination of this knowledge. It deserves also to be emphasized that a substantial part of this book is devoted to the Financial Markets so determinant to the World Economy for good and for evil. In short: a book indispensable reading for senior and beginner researchers and professionals in economics, financial management and network analysis.

Keywords – Financial data mining, Market graph analysis, Market network analysis, Mathematics for economics and finance, Network modeling in economics, Network modeling in finance.

Related subjects – Applications, Complexity, Database Management & Information Retrieval, Financial Economics, Mathematics.

1. The review

This book is composed of fourteen chapters:

-Experimental design problems and Nash equilibrium solutions

-A Variational Approach to the Evolutionary Financial Equilibrium Problems with Memory Terms and Adaptive Constraints

-Robustness of sign correlation in market network analysis

-Two Classes of Games on Polyhedral Sets in Systems Economic Studies

-Densely Entangled Financial Systems

-Sigmoid Data Fitting by Least Squares Adjustment of Second and Third Divided Differences

-Financial Modeling under Multiple Criteria

-Agent-based Models of Stock Exchange: Analysis via Computational Simulation

-Network Centrality and Key Economic Indicators: A Case Study

-Network structures uncertainty for different markets

-Complexity Analysis and Systemic Risk in Finance: Some Methodological Issues

-A Dynamic Network Economic Model of a Service-Oriented Internet with Price and Quality Competition

-European Business Cycle Synchronization: A Complex Network Perspective

-A Novel Banking Supervision Method using the Minimum Dominating Set.

In general, the whole book is devoted to the use of network models to investigate the interconnections in modern economic systems, hopping that this will lead to a better understanding and explaining of some economic phenomena, in particular in what concerns their financial issue.

A special attention is given to the Financial Markets namely to the banking system and the stock exchange. Of course this is imperative in nowadays times and, in accordance, the models presented are also supposed to help to analyze the financial crisis and the risk in finance.

Also remarkable is the presence of Game Theory in this book. It became indispensable in markets analysis and the authors that used it here made it in a very innovative way.

Notable also the explicit reference to Complex Network in the chapter "European Business Cycle Synchronization: A Complex Network Perspective", perceiving that business cycle synchronization, at a global level, is a complex network problem. In fact this idea of complex network problems is present, either explicitly or implicitly, along the whole book.

Of course an approach of this kind, that is, networks in complex problems, demands a broad spectrum of tools. Here, Mathematics, Statistics, Operations Research, Simulation, Data Mining, Game Theory, Networks, Complexity, Database Management & Information Retrieval, Finance and Economics are present. All these tools are used with dexterity and purpose by the several authors, who expose very clearly their applications, allowing to the readers even with some mathematical difficulties, their perfect understanding.

This book may be said to be complete in the sense that, not presenting of course the whole kind of possible analysis methodologies in this field, it gives a small and diverse set universal in the quantity of the problems approachable through them.

So "Network Models in Economics and Finance" is a very good handbook for researchers and professionals in this field.

2. Overall Review

A book dealing with a very important subject, scientifically rigorous and very well written, that is an indispensable reading for senior and beginner researchers and professionals in economics, financial management and network analysis.

Reference

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