Efficiency and predictability on international soybean oil prices

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Abstract: - In analysing the efficiency, non-linearity and predictability of soybean [Glycine max (L.) Merr.] oil price series structural breaks were identified. The efficiency of the market in its weak form was then analysed using automatic variance ratio for small samples. Group Method of Data Handling (GMDH) polynomial neural networks, the Box Jenkins Method and Genetic Algorithms were tested for their ability to predict return on a monthly basis. The analysis suggested an inefficiency in weak form and some predictability of the market. The Diebold-Mariano, used to discriminate amongst models according to their accuracy, indicated that the combined use of linear (ARIMA) and non-linear (e.g., multilayered and self-organizing artificial neural networks of the GMDH and Genetic Algorithm type) techniques significantly improved the market prediction.

Key-Words: market efficiency, soybean oil, predictability.

1 Introduction

Soybean [Glycine max (L.) Merr.] is one of the oldest food sources known to humans. In 2011, some 102.99 million ha planted to soybean worldwide produced 260.92 Tg of soybeans (FAO, 2013), of which just under 29% were produced in Brazil. Brazil is the world's largest producer of biodiesel and one of its main consumers as well. Brazil has prioritized the production and use of soybeans as raw material for this industry, thereby generating 17-million biodiesel barrels/year, and requiring 3 million hectares for soy production in order to respond to current demand. This represents approximately 12.30% of the cultivated area in Brazil.

This paper addresses the efficiency and predictability of international soybean oil prices. A market is considered efficient when the price system reflects the availability of the full database of information to all players (Fama, 1970). If the database only includes past prices, efficiency is deemed to be weak. The interest in predicting price behavior is probably as old as the markets themselves, so it is not surprising that the relevant literature is wide and significant (Ferson, 2007). A combination of linear and non-linear techniques has been employed to anticipate financial time series and are employed with growing frequency in empirical testing studies. The use of Artificial Neural Network (ANN) techniques, Auto-Regressive Integrated Moving Average (ARIMA) models and Genetic Algorithms (GA), for example, has drawn some attention.

Combining predictive methods for developing pondered averages has long been discussed (Bates and Granger, 1969; Dickinson, 1973; Newbold and Granger, 1974; Bunn, 1978). Various studies have shown that the combined use of linear (e.g., ARIMA) and non-linear (e.g., multilayered, self-organizing artificial neural networks and Genetic Algorithms) techniques significantly improve prediction results, compared to single model predictions. The objective of the present study was to compare the predictability of international soybean oil price equity markets using Group Method of Data Handling (GMDH), Box-Jenkins and Genetic Algorithm (GA) method for monthly return data series.

One of the oldest food sources known to humans, soybean contains, on average, about 40% protein, 23% carbohydrates, 20% oil, 5% minerals, 4% fiber and 8% moisture (Gopalan et al., 1974). While soybeans have many uses, they are mainly pressed to extract oil, after which a soybean meal remains (Qiu and Chang, 2010). Soybean oil can be used for the production of edible oils such as kitchen oil, salad oil and others through refining and more extensive processing. Soybean oil is also used for the production of printing ink and biodiesel. Soybean meal is mainly used as a component of livestock feed. Soybean is one of the most highly valued oilseed crops in the world (Sinh & Shivakumar, 2010). On the world stage, soybean accounts for 41.64 Tg y-1 of oil (FAO, 2013), putting it far ahead of all other field crops raised for oil extraction (Table 1).

Table 1. Oil production from global field crops during 1961 and 2011

Crop	Oil prod.(Tg y^{-1})		% of total	% change
	1961	2011	2011	1961-2011
Soybean	3.04	41.64	28.88%	1.269.74%
Rapeseed	1.1	22.33	15.49%	1.930.00%
Sunflower	1.9	13.33	9.25%	601.58%
PalmKernel	0.49	5.86	4.06%	1.095.92%
Peanut	2.51	5.67	3.93%	125.90%
Cottonseed	2.19	4.99	3.46%	127.85%
Coconut-copra	1.63	4.31	2.99%	164.42%
Olive	1.36	3.42	2.37%	151.47%
Maize	0.35	2.34	1.62%	568.57%
Castorbean	0.22	1.07	0.74%	386.36%
Sesame	0.4	1.01	0.70%	152.50%
Linseed	0.85	0.52	0.36%	-38.82%
Safflower	0.09	0.13	0.09%	44.44%
Others	2.44	37.54	26.04%	1.438.52%
Total	18.57	144.16*	100.00%	676.31%

*Total of 2009 production. Source: FAO (2013)

Global soybean imports have been rapidly increasing, particularly given the growing demand for soybean in Asia (Chianu et al., 2010). The demand surge (i.e., a 21-fold increase in soybean imports between 1994 and 2011) stems largely from China, whose domestic production (5.55% of world) is insignificant, but whose imports have skyrocketed in the last ten years (Figure 1).

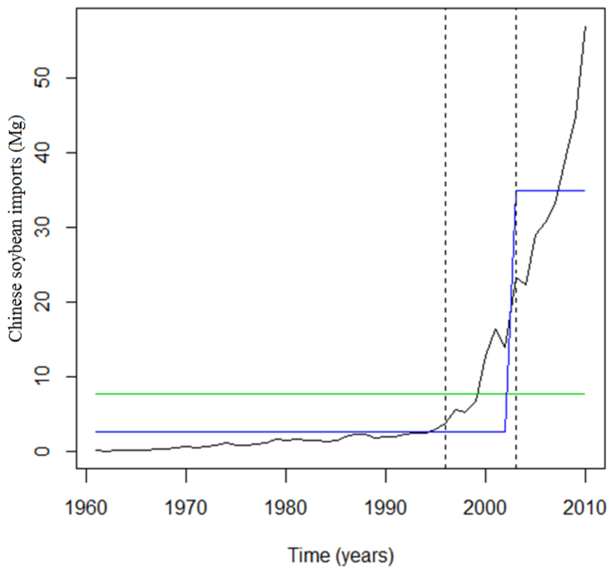

Figure 1 – Structural break for Chinese soybean imports [1961–2010]. Source: plotted from data drawn from FAO (2013)

Two ruptures, and three regimes exist in China´s importation of soybean (Figure 1). A first behavioral change occurs in this series as of the 43rd observation (2003). The demand surge was triggered by China's 2002 WTO membership, which ended border tariffs and, in turn, boosted trade. The increasing global demand for soybean has been met through a strong supply response from Brazil and Argentina. Soybean cultivation in Brazil is expected to expand further in the coming decades, mainly in response to the growing demand in Asia (Smaling et al., 2008). In 2011, the soybean production of the United States, Brazil and Argentina were: 83.17, 74.81 and 48.87 Tg, respectively, or 79.28% of world production.

In 2011 world pork production was 110 Tg, of which China produced 46.84% (51.53 Tg; FAO, 2013). Pork remains the preferred meat in China though the shares of poultry and beef have increased. This huge Chinese production of meat, influenced by the rapid increase in the power consumption of the Chinese people, is associated with a high share of soybean meal in animal diets (Table 2). This has significantly increased the demand for soy, resulting in soybean and soybean oil prices.

Table 2. China's feed composition (2006-07 year average)

Feed Ingredients*	Tg	Share
Maize	99	37.00%
Sweet Potatoes	35.6	13.30%
Soybean	29.2	10.90%
Vegetables, Other	27.1	10.10%
Cassava	15.4	5.70%
Rice	10.1	3.80%
Brans	9.4	3.50%
Potatoes	6.5	2.40%
Wheat	6.2	2.30%
Other ingredientes	29.3	11.00%
Total	267.7	100.00%

.*Include cereals, starchy roots, sugar crops, pulses, oil crops, and vegetables. Regarding oil crops, beans/seeds, cake (meal), and vegetable oils are distinguished as different ingredients in this table. Animal originated ingredients (livestock and aquatic products) are not included. Source: Masuda, Goldsmith & IFAMR (2012)

An important alternative in diversifying the world's energy matrix and decreasing oil and oil derivative dependence, biodiesel generates several advantageous economic, social, and environmental offshoots. It can generate both employment and rent, decrease greenhouse gases emission, and increase a producing country's currency value, both through its export, and reduced oil imports. Brazil, the largest producer and one of the main consumers of biodiesel in the world and has prioritized the use of soybeans as raw material for this industry.

On the other hand, biodiesel has raised concerns since some evidence points to a causality relationship between biodiesel and agricultural commodities prices (Senauer, 2008; Zhang et al., 2009, 2011). While Yang et al. (2008) have stated that higher soybean prices are largely due to increases in the price of oil, and increased demand for bio-fuels, in contrast, Mitchell (2008) suggested that, despite differences in approach, many studies have recognized that bio-fuel production has been a determining factor in the increase of food costs. Lipsky (2008) pointed out that the International Monetary Fund (IMF) has estimated that the increased demand for bio-fuel was responsible for 70% of the increase of corn prices and 40% of that of soy. On the other hand, Risso (2011) concluded that the recent increase in the cost of soy and its derivatives was closely connected to the Yuan: US dollar ratio, and especially connected to Chinese economic growth.

In another hand, the efficient market hypothesis divides efficiency into three categories: weak form, semi-strong form and strong form. Weak form efficiency is based on a dataset of information that only includes the price or stocks return history. The semi-strong form considers a set of information that only includes the public knowledge available to all participants in the market. Strong form efficiency includes all information obtained by any participant in the market.

Other definitions of market efficiency have been suggested by Rubinstein (1975), Jensen (1978), Beaver (1981), Black (1986), Dacorogna et al. (2001), Malkiel (2003), Timmermann & Granger (2004) and Milionis (2007). Since there is no consensual definition for the pattern of market efficiency, we adopted the definitions provided by Fama (1970), which emphasize both speed and precision of price adjustment to new information.

Since the pioneering research of Lo and MacKinlay (1988), the variance ratio test has emerged as the main tool to test the random walk hypothesis and, consequently, weak form market efficiency. As a consequence, Charles & Darne (2009b) provide an extensive review of its recent evolution. In order to capture both sides of the random walk, the variance ratio test as developed by Lo and MacKinlay (1988) has two null alternatives: (a) independent and identically distributed innovations as a normal distribution (i.i.d.); and (b) non-correlated but weakly dependent innovations with the possibility of heteroscedasticity on their frequency distribution. The crucial point on this test is that if the return of one stock item follows a purely random walk, the return variance of a period q is q times the variance of the first difference. Thus, the null hypothesis (H0) in this test states that the variance ratio equals 1.

After Lo and MacKinlay (1988) several improvements have been made to the test, including the work of Chow and Denning (1993) who suggested a multiple variance ratio test, differing from the previous in that one can simultaneously verify if all variance ratios equal 1. Another remarkable innovation in the variance ratio test was developed by Wright (2000) who suggested the use of non-parametrical variance ratio tests based on positions and signals of time series.

Another refinement of the variance ratio test was the automatic determination of investment horizons, initially suggested by Choi (1999), using the optimal rule for estimating the spectral density on zero frequency, developed by Andrews (1991). Kim (2009) assessing this test’s performance suggested using the wild bootstrap method to improve its use with small samples. The test suggested by Kim (2009) did not show any distortions in size and the power was substantially greater than that of other tests (e.g., Chen and Deo, 2006; Chow and Denning, 1993). The importance of this test is that it does not require random investment horizon choices, which could lead to contradictory results depending on the values chosen. In order to control the test’s dimension, other procedures have been suggested in the literature (Richardson and Smith, 1991; Whang & Kim, 2003; Kim, 2006; Kim & Shamsuddin, 2008).

Another form to test the market efficient hypothesis is use the GMDH. Based on an algorithm dating back to 1960s, the GMDH method (Group Method of Data Handling) is a mathematical method to estimate states in a system, controllers’ exits and performers functions (Ivakhnenko, 1969). The algorithm initially suggested can be considered self-organized and of inductive propagation for the solution of practical and complex problems. Besides, it is possible to obtain a mathematical model for the process from sample data observations. This can be used when identifying and recognizing patterns, or even to describe the process itself.

Using GMDH-like self-organizing networks has succeeded to predict time series in a wide range of fields of study (Ahmadi et al. 2007). Mottaghilab et al. (2010) noted good results with this type of network in specific domains, particularly engineering and economics. Most GMDH algorithms use polynomial reference functions. A general connection between entry and exit variables can be expressed by the Volterra functional series, an analogue of the Kolmogorov-Gabor polynomial:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1} \sum_{k=1}^{n} \beta_{ijk} x_i x_j x_k + \xi.$$

Where,i, j, k,are the time; x_i,x_j,x_k are the endogenous variables, β_0, β_{ij} and β_{ijk} are the polynomial coefficients and ξ is the error.

The Ivaknenko (1969) algorithm was developed as a vehicle to identify linear and non-linear relationships between inputs and outputs, thus generating a structure tending to be optimal, from a successive process of several data manipulations, via the incorporation of new layers.

The GMDH model can be visualized as a combination of neural networks and stochastic concepts (Valença, 2005). Implemented with activating functions in the neurons of the hidden layers, GMDH networks use a selection criterion to decide how many layers will be built. In the original state, each neuron of the hidden layer to be built receives two entries and must activate a 2nd degree polynomial. Consequently, a polynomial exit function will be generated via the combination of each pair of these entry neurons. The complexity of such polynomials depends on the number of layers, i.e., if there are two layers, we have a 4th degree polynomial function; for three layers, there will be an 8th degree function, and so on. Thus, such networks are termed polynomial, and the resulting model represents a polynomial function. Other form to test efficient market hypothesis is the The Box-Jenkins Method.

Developed in the early 1970s, the Box-Jenkins or Autoregressive Integrated Moving Average (ARIMA) model (Box et al., 1970), is a complex interactive procedure that generates an integrated moving average. This autoregressive model, adjusts for seasonal and trend factors, besides estimating adequate pondering parameters, testing the model and repeating the cycle, if need be.

In economics, there are stationary (e.g., log-returns) and non-stationary series (e.g., stocks return and GDP growth), the latter of which does not vary around the same average and may have a deterministic or stochastic nature. A non-stationary data series with a stochastic trend moves around floating averages and has the configuration:

$$y_t = y_{t-1} + \varepsilon_t$$

Where, $y_{t-1}$is the endogenous variable in *t*-1, ε_t is the error.

The concept of stationarity must be kept in mind to estimate a time series, especially for ARIMA models. The stochastic process, or the time series, $\{y_t, t \in Z\}, Z = \{0, \pm 1, \pm 2 \dots\}$ is weakly stationary if (i) $E|y_t|^2 < \infty$, (ii) $E(y_t) = \mu$ for all $t \in Z$, and (iii) $E(y_t - \mu)(y_{t-j} - \mu) = \gamma_t$.

The first condition only states that the second non-centred moment must be finite, though it is unequal for all periods. The second condition states that the mean is the same for all periods, even if the distribution for the random variable changes through the course of time. The third condition states that variance remains the same across all periods, while auto-covariance depends on the distance between observations, but not the variance. Other form to test efficient market hypothesis is the use of combined methods use for predicting time series.

The traditional approach in predicting physical parameters involves choosing a prediction method which outperforms other available methods, and apply it to some specific situations (Hammoudeha et al., 2012). Choosing the appropriate method depends on the characteristics of each data series studied as well as on the application type (Makridakis et al., 2008). However, the logic behind this approach is the notion that a “best” method exists and can be identified (Winkler and Makridakis, 1983). An alternative to the traditional approach is gathering information concerning different prediction methods by aggregating each prediction, thus eliminating the issue of having to select one single prediction model.

Under study for some time, the use of combined predictions, the methods to be used in such combinations, and the use of pondered averages have been discussed at length (Bates and Granger, 1969; Dickinson, 1973; Newbold and Granger, 1974; Bunn, 1978. Newbold and Granger (1974) noted that Bates & Granger (1969) were the pioneers of studying the combination of predictions, developing a method for combining both predictions from one linear combination, pondering one prediction with a weight w and another prediction with the weight (1 – w). Thus, the combined prediction (Pc) was obtained as:

$$P_c = w \cdot P_1 + (1 - w) \cdot P_2$$

where, P_1 and P_2 are the predictions to be combined; however, if w = 0.5, Pc simply becomes the arithmetical average of P_1 and P_2. The averaging of predictions was also defended by Winkler and Makridakis (1983), Taylor and Bunn (1998) and De Menezes et al. (2000). However, despite all these arguments, the idea of combining predictions by other methods to reduce prediction error has been widely studied.

In this context, Eq. 3 shows that different weights are applied to different predictions, in such a way that the largest weight is allocated to the individual prediction with the smallest discrepancy. This way, determining the weight w results in minimizing the prediction errors' combined variance. Consequently, the minimum variance method, where the prediction variance is combined according to the weight w was developed:

$$\grave{U} = \sigma_c^2 = w\sigma_1^2 + (1 - w)^2\sigma_2^2 + 2pw\sigma_1(1 - w)\sigma_2$$

where σ_1^2 and σ_2^2 are the errors variances for each individual prediction. Newbold & Granger (1974) carried on with the study initiated by Bates & Granger (1969), and, based on their premises, developed a combination of n techniques:

$$\mathrm{P_c} = \mathrm{w_1P_1} + \mathrm{w_2P_2} + \mathrm{w_3P_3} + \cdots \mathrm{w_nP_n}$$

where, wi is the weight allocated to each the ith prediction (Pi), and Pc is the combined prediction. Regarding the weight determination, the same guidelines were followed as for the previous studies, proving that the procedures described above were valid for determining the weights in the combination of n techniques. Libby & Blashfield (1978) and Bates and Granger (1969) concurred that most of the time a greater prediction precision was achieved when considering two to three techniques.

Evaluating the method developed by Newbold and Granger (1974), Winkler & Makridakis (1983) analyzed the pondered combinations between ten techniques, thereby confirming their predecessors' proposals regarding n techniques. Nevertheless, even stating that accuracy increases, according to the number of combined techniques, the authors observed that the use of four to five combined techniques would lead to saturation, at which point no further improvement in prediction accuracy could be achieved. Newbold and Granger (1974) considered, in their research, the residues of individual predictions in obtaining the weight of the prediction (wi):

$$\mathrm{w_i} = \frac{\left(\sum_{i=1}^{i=t} e_i^2\right)^{-1}}{\sum_{j=1}^{j=n}\left(\sum_{i=1}^{i=t} e_i^2\right)^{-1}}$$

where, n is the number of techniques that are combined, t is the number of periods included for determining the prediction weights, and ei are the prediction residues – obtained from the differences between observed and predicted data.

Nearly four decades after the beginning of the predictions combination theory research in the field still continues (e.g.: Sallehuddin and Shamsuddin, 2009); Jiang et al., 2010; Chen, 2011; Coshall and Charlesworth, 2011), primarily towards improving or developing new techniques that are clearly non-linear. In this context, we sought some empirical evidence where the combined use of predictions was used for predicting financial and non-financial time series (Table 3).

Table 3: Empirical evidence of the combined use of predictions for predicting financial and non-financial time series

Authors	Method	Results
Winkler and Smakridakis (1983)	Exponential Smoothing and	Combined use showed a better result when compared to individual prediction
Reeves et al. (1988)	Exponential Smoothing and ARIMA	Combined use of different methods (*e.g.*, exponential smoothing and ARIMA) more efficient when predicting time series, than when used individually.
Fiordaliso (1998)	ARIMA, OLS, Fuzzy System, Nearest Neighbor Method*	The use of a non-linear model for combining predictions showed better results than a linear model
Xiong et al., (2001)	Fuzzy System based in Takagi–Sugeno, simple average, pondered average and neural networks.	While individual prediction models' prediction capacity were very similar, their combined use in predictions showed only marginally superior results.
Kanas and Yannopoulos (2001)	Single layered ANNs and Multilayered Artificial Networks	The use of multi-layered non-linear ANNs showed better prediction of index series (*Jones Industrial Average and - DJ and Financial Times All Share Index -FT)*) outside the sample than Linear Neural Networks
Terui and Van Dijk (2002)	AR and TAR (threshold autoregressive)	In economic models the combined use of linear and non-linear models was more accurate than either alone.
He and Xu (2005)	GMDH and Artificial Neural Networks	Self-organizing polynomial artificial Neural Networks, GMDH, showed superior results for prediction of Chinese economic parameters when

		combined rather than individually.
Amjady and Keynia (2008)	ANNs and Genetic Algorithm	A hybrid model, combining ANN techniques and the genetic algorithm, were significantly better in predicting non-linear time series, than either technique alone.
Chan, et al. (2010)	Exponential Smoothing and ARIMA and VAR	The combined use of predictions, using the CUSUM method improved the combined models' predictions performance
Shafie-khah et al. (2011)	ANN and ARIMA models	The hybrid use of ARIMA predictions combined with ANN predictions provided a significant improvement in precision when predicting prices time series
Cao et al. (2012)	ANN and ARIMA models	The ANNs showed better predictive ability when compared to the ARIMA models when predicting time series.

*This is a deterministic nonlinear approach that uses the series entry pattern in order to project it outside the series
OLS means Ordinary Least Squares method, ANN means Artificial Neural Network method ,ARIMA means Autoregressive Integrated Moving Average model and VAR means Vector Autoregressive method

Table 3 shows some evidence that prove that the combined use of linear (ARIMA) and non-linear (such as multilayered and self-organizing ANNs – GMDH type) techniques significantly improve the prediction results, when compared to unitary predictions.

2 Materials and Methods

Monthly international soybean oil prices were analyzed over a period determined using the Structural Change test (January 1957 to December 2014), which included 696 observations.

The problem of detecting structural changes in linear regression relationships has been an important topic in econometric and statistical research (Zeileis et al. 2001), considering that a careless analysis can result in incorrect inferences in causality tests, co-integration and acceptance of incorrect models (Covas, 1997). The latter author states that these tests can determine the way exogenous shocks or political regime changes are felt in the behavior of some economic indicators.

In order to adequately treat time series, several tests have made it possible to identify and estimate the moments of structural breaks. Early tests [e.g., Chow, 1960 and CUSUM (Brown et al. 1975) were flawed in drawing upon an a priori knowledge of where the structural break was. The second class of tests allows the detection of several types of breaks for parameters of interest and the number of breaks in the series need not be specified (Covas, 1997). The last five decades have seen numerous empirical studies regarding the market's efficiency. Several refinements have been suggested in order to increase the variance ratio test robustness of heteroscedastic procedures, as well as decrease their size distortions and improve their power. Tests that consider the whole variance ratio statistics' distribution have been suggested in order to solve the size super-dimensioning problem that results from using the same set of data for different inferences (Richardson and Smith, 1991; Chow and Denning, 1993; Chen and Deo, 2006).

Initially suggested by Choi (1999), another refinement of the variance ratio test was the automatic determination of the investment horizons, using the optimal rule in order to estimate the spectral density for zero frequency (Andrews, 1991). Kim (2009) analysed this test's performance and suggested using the wild bootstrap method to improve its performance for small samples. This alternative method resulted in the text no longer showing distortions in size and being much more powerful than in other tests (e.g., Chen and Deo, 2006; Chow and Denning, 1993). The importance of this test lies in the fact that random choices, which can lead to contradicting results, are no longer needed for investment horizons (Kim, 2006, 2009; Charles et al. 2011). In the present study we used the variance ratio test of Kim (2006, 2009). After determining the period of analysis, we determined the periods of training (75% of the period) and testing (25% of the period). We then applied the Box-Jenkins Model (ARIMA) and two nonlinear models: an ANN and a genetic algorithm (GA). In order to evaluate the predictions' accuracy the δ^2 statistic (Ivaknenko et al., 1993) was employed:

$$\delta_i^2 = \frac{\sum_{i=1}^{i=N}(y_i - \widehat{y}_i)^2}{\sum_{i=1}^{i=N}(y_i - \bar{y})^2} \to min.$$

where, N is number of observations, y_i is return during i period, $\widehat{y}_i$ is computed values according to the model $\bar{y}$ is the mean value.

A value of $\delta^2 \leq 0.5$ represents excellent accuracy, $0.5 < \delta^2 < 0.8$ represents satisfactory accuracy, and $1.0 < \delta^2$ represents misinformation and a poor models.

To compare the efficiency of predictability at ANN, ARIMA and GA models, we used the sample coefficient of determination R2, the MSE and MAE.

$$R^2 = 1 - \frac{\sum_{i=1}^{i=N}(\widehat{y}_i)^2}{\sum_{i=1}^{i=N}(y_i - \bar{y})^2}$$

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{i=N}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{i=N}\left|\sqrt{y_i^2} - \sqrt{\hat{y}_i^2}\right|$$

Additionally, we analyzed the Theil's inequality coefficient (U) whose numerator is the MSE, but whose denominator is such that $0 \leq U \leq 1$, where $U = 0$ would represent a perfect match between predicted and observed values, while $U = 1$, would represent the worse possible match between predicted and observed values:

$$U = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{i=N}(y_i - \hat{y}_i)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{i=N} y_i^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{i=N} \hat{y}_i^2}}$$

We analyzed the trend and variance proportions (U^M and U^S, respectively) of U proportion, which allow one to decompose the error into its characteristic sources (Pindyck and Rubinfeld, 1991). The value of U^M addresses the possible systematic error, measuring how the series' average values deviate from each other. Whatever value U takes, one expects U^M to be close to 0, whereas if $U^M > 0.1$ this would indicate the presence of a systematic trend, requiring a revision of the models.

$$U^M = \frac{\left(\bar{y}^S - \bar{y}^A\right)^2}{\frac{1}{T}\sum_{t=1}^{t=T}\left(\bar{y}_t^S - \bar{y}_t^A\right)^2}$$

$$U^S = \frac{\left(\sigma^S - \sigma^A\right)^2}{\frac{1}{T}\sum_{t=1}^{t=T}\left(\bar{y}_t^S - \bar{y}_t^A\right)^2}$$

where, $\bar{y}^S, \bar{y}^A, \sigma^S$ and σ^A are, respectively, the mean and the standard deviations of the estimated and observed values. The variance proportion U^S, indicates the ability to replicate the variable of interest's degree of variability (Pindick and Rubinfeld, 1991) . If U^S is high, it indicates that the effective series floated substantially, whereas a low value would indicate very little floatation. That high U^S would also be concerning and could lead to reviewing models.

When comparing two forecasts, the question of whether the predictions of a given model, A, are significantly more accurate, in terms of a loss function g(.) , than those of the competing model, B arises. The Diebold-Mariano test aims to test the null hypothesis of equality of expected forecast accuracy against and alternative of differing forecasting ability across models (Diebold and Mariano, 1995) . The null hypothesis of the test can thus be written as:

$$d_t = E\left|g(e_t^A) - g(e_t^B)\right| = 0$$

where e_t^i refers to the forecasting error of model i when performing h–steps ahead forecasts. The Diebold-Mariano test uses the autocorrelation-corrected sample mean of dt in order to test for we use the equation (14). If n observations and forecasts are available, the test statistic is, therefore,

$$S = \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}}$$

where,

$$\hat{V}(\bar{d}) = \frac{1}{n}\left(\hat{y}_0 + 2\sum_{k=1}^{k=h-1}\hat{y}_k\right)$$

and

$$\hat{y}_k = \frac{1}{n}\sum_{t=k+1}^{n}(d_t - \bar{d}_t)(d_{t-k} - \bar{d}_t)$$

under the null hypothesis of equal forecast accuracy, S is asymptotically normally distributed.

3. Results, Discussion, and Conclusions

(12)

Testing the hypothesis of the existence of structural breaks in the time series showed H0 to be was rejected, implying the vector b variance to be constant throughout the whole series (stats = 6.3623, P < 0.0001). This denotes the existence of structural breaks in the time series. The Bai & Perron (1998) method, which allows one to simultaneously estimate multiple breaks as well as their not previously known dates in a data series was used to find breaks in the international soybean price data. This procedure returned 2 break-points in the time series from January 1957 to December 2014 (Figure 2). With m breaks, there are m+1 regimes, hence the series under study showed 3 regimes (Table 4):

Table 4: Dates of each regime identified

Regime	From	To
1st	January 1957	June 1973
2nd	July 1973	November 2003
3rd	December 2003	November 2014

The main structural break occurred in November 2003, the same structural break that occurred in Chinese soybean imports (Figure 1) and was likely associated with the demand surge triggered by China's 2002 WTO membership, ending border tariffs, boosting trade, and thereby raising demand for soybean. Consequently, the cost of this commodity rose from roughly $400 US (blue line, Figure 2) on average, to above 850. This implies an increase in volatility after this structural break. After identifying the structural breaks, and their respective dates, the log-returns, on a monthly basis, where calculated, and evaluated statistically (Table 5).

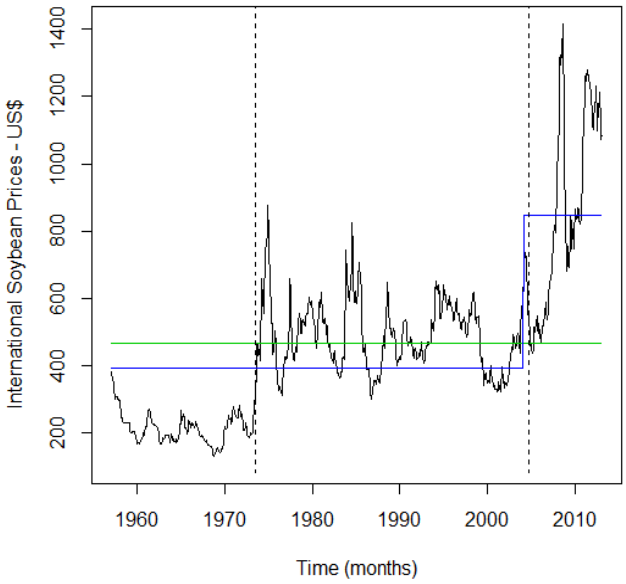

Figure 2: Structural Breaks on international soybean price´s

Table 5: Descriptive statistics and the automatic variation coefficient for small samples of log-returns on international soybean prices for each one of the three identified regimes.

Reg.	Min.	Max.	Ass.	Kurt.	Std. Dev.	Kim (2006, 2009) Stat.	*p*-value
1st	-0.172	0.182	0.323	1.806	0.057	2.267	0.000
2nd	-0.195	0.343	0.609	2.355	0.067	2.233	0.040
3rd	-0.253	0.146	-0.670	1.605	0.065	4.196	0.000

Table 5 shows the greater data volatility of the three regimes, where the returns vary from -0.2534 (min) and 0.1462 (max). There was excessive of kurtosis (1,6049), making for platykurtic returns with a moderate asymmetry to the right (-0,6701). These results imply a rejection of the H0 of the automatic variation coefficient test for small samples (Kim, 2006). The H0 being rejected indicates that, for this regime, the series' returns show a random walk behavior. This implies that for all periods, the log return showed characteristics that are non-compatible with the efficiency hypothesis of the market. It denotes inefficiency, indicating that for that opportunity there would be the possibility of abnormal gains in this market (Fama, 1970).

After identifying this structural break, the returns for the periods between January 1957 and November 2003 were eliminated. Among the 672 observations that initially were used, 563 were eliminated, and 109 were kept. The remaining return series was separated in two new series: the first 75% part was destined for training and the last 25% part of observations (48 months, in the period between January 2011 and December 2014) were used to test the series capacity to predict. Despite the fact that the coefficient variation test indicated that international soybean prices was inefficient in its weak mode, this does not mean that it is necessarily predictable. Thus, we initially tested predictability using a linear model (ARIMA), and two non-linear methods (Genetic Algorithm – GA - GMDH Polynomial Neural Networks), as well as testing their combination (Eq. 6).

Table 6. predictions results in *t*+1 of the log returns for international soybean oil prices January 2011 and December 2014

Method	R^2	MSE	MAE	U	U^M	U^S	Ivakhnenko
GA*	0.089	0.003	0.037	0.032	0.003	0.000	0.989
ARIMA	0.010	0.003	0.030	0.039	0.021	0.010	1.130
GMDH	0.084	0.004	0.038	0.058	0.001	0.000	1.940
Combi	0.152	0.002	0.035	0.031	0.003	0.000	0.907

*GA means Genetic Algorithm

In Table 6 we can see that the predictions made by the Genetic Algorithm method being superior when we compared R^2, as well as the signals, the Ivaknenko criterion (Eq. 7) was better than the one for predictions made by the ANN (GMDH). The criterion values for the ARIMA and GMDH models would label these models as providing disinformation; therefore, it would be inadequate to only use this method for predicting returns for this period. On the other hand, the combined model predictions (Eq. 6) showed greater accuracy (higher R2, MSE, MAE, and U) than any of the individual models, and the results for the Ivakhnenko criterion could be considered satisfactory.

In order to verify that the combined use of predictions was actually more accurate than any of the individual models, the Diebolt and Mariano test was applied to compare prediction results (Table 7). The Diebolt and Mariano test compares the accuracy of both predictions, making it necessary to test each prediction against the others. The superior results of the combination technique over individual techniques (P = 1.000) indicate some predictability for the returns of the international soybean oil prices, which corroborates the supposition that the market is inefficient in its weak mode. Indeed, for all statistical tests the accuracy achieved with a combined use of predictions was significantly greater than any individual methods. The ARIMA model's predictions were less accurate than those achieved with the Genetic Algorithm, and less than the ones obtained for GMDH-ANN. These results are confirmed by the Ivakhnenko criterion (Table 6). The results obtained by the combined use of predictions were considered to be satisfactory, corroborating much evidence pointing to the fact that the combined use of predictions shows better results than unitary predictions (Winkler & Smakridakis, 1983; Reeves et al., 1988; Fiordaliso, 1998, Xiong et al., 2001, Terui and Van Dijk, 2002; He and Xu, 2005; Amjady and Keynia, 2008; Chan et al., 2010; Shafie-khah et al., 2011; Cao et al., 2012).

Table 7. Diebolt and Mariano's test results for predictions accuracy equality.

	Arima (*y*)			Genetic Algorithm (*y*)			GMDH-ANN (*y*)		
Method	*x<y*	*x=y*	*x>y*	*x<y*	*x=y*	*x>y*	*x<y*	*x=y*	*x>y*
	sig.	*Sig*	*sig*	*Sig*	*sig*	*sig*	*sig*	*sig*	*Sig*
Comb (*x*)	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
Arima(*x*)				1.00	0.00	0.00	1.00	0.00	0.00
GA (*x*)							0.00	0.00	1.00

One concern with model validation is whether the model maintains its predictive ability when working with data different from those used in training. This is one reason why the data series are divided into two parts, one for building and training the model and the other for validation and testing. However, this procedure only allows testing developed model to occur once. To increase model reliability it is recommended to use other data. Thus, to validate the model is necessary to work with data similar to the original series, usually randomly generated. It is understood that if the developed models are unable to predict values similar to the original series, then the success of the model can be attributed to a causal factor in the series, where the error favorably contributes to the predictive ability of the model. Thus, in order to test the predictive ability of the developed model, we designed a generator of random values able to reproduce the behavior of soybean prices. Initially, we analyzed soybean prices in order to find out a behavior pattern in the data — the predictable. After evaluating the data, it was found that the price of soybeans could be estimated using a linear regression:

$$X_{t+1} = 0.98X_t + 21.64 + \xi$$

where, Xt is the price of soybeans in period t, and ξ is the error As expected, a random error regression was found, whose error had a similar distribution to a normal curve ($\chi^2 = 4.48$, P = 0.11). Once the normal distribution of the error was identified, it was possible to generate random values similar to actual sales prices of soybeans.

Finally, it is common to observe sequences of growth or declines in prices in time series. These sequences are not captured by random models. When generating random values it is expected that these values remain intercalated above and below the average with no sequences of growth or decline behavior. Thus, the random values were changed to positive or negative according to the values found in the original time series. This procedure allowed the capture of sequences of growth or decline prices, allowing the generation of random values similar to the original prices of soybeans. The uses of similar generated random data allow us to verify if prediction models are reliable (Table 8).

Table 8. predictions results in *t*+1 of the log returns for international soybean oil price´s January 2011 and December 2014

Method	R^2	MSE	MAE	U	U^M	U^S	Ivakhnenko
Genetic Algorithm	0.019	0.009	0.076	0.080	0.001	0.003	1.125
ARIMA	0.240	0.007	0.070	0.076	0.001	0.008	0.932
GMDH	0.131	0.015	0.094	0.070	0.006	0.000	1.877
Combination	0.131	0.007	0.066	0.059	0.000	0.002	0.874

The combination model outperformed all others, as it showed superior accuracy statistics (except adjusted R^2; Table 8), particularly with respect to the Ivakhnenko criterion (Eq.7). This clearly shows the combination model to be better than its competitors.

4 Final Considerations

Secondary data derived from international soybean oil prices were used in this research. Initially, the structural breaks hypothesis was tested on the data series. Two structural breaks were found, forming three different regimes. The main structural break occurred in November 2003, possibly as a result of a surge in demand arising from China's abolition of border tariffs following their 2002 WTO membership. This, in turn would have boosted trade, thus raising demand for soybean, and, as a consequence, raising the cost of this commodity.

After identifying the structural breaks in the time series, the Market Efficiency Hypothesis was tested. The automatic variation coefficient for small samples was used; as initially proposed by Fama (1970) and after by Kim (2006). The results point to inefficiency in the weak mode, with 1% significance for that market. In this regard, monthly inefficiency denotes significant arbitrage opportunities. The combined use of linear (ARIMA) and non-linear (GA and ANN) techniques was employed to choose a model to find the arbitrariness opportunities for this commodity. The prediction in *t*+1 of the monthly return by the combined model showed results that were clearly more accurate than any individual component model. This result was confirmed by the Diebolt and Mariano test, which indicated that the combined use of these predictions afforded was significantly greater accuracy than the individual methods.

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