XVI SemeAD
Seminários em Administração

outubro de 2013
ISSN 2177-3866

Comparative Modeling Assessment of Aluminum Price Forecast

JOÃO BOSCO BARROSO DE CASTRO
USP - Universidade de São Paulo
joaobosco.castro@uol.com.br

ALCIDES CARLOS DE ARAUJO
USP - Universidade de São Paulo
alcides.carlos@yahoo.com.br

ALESSANDRA DE AVILA MONTINI
USP - Universidade de São Paulo
amontini@usp.br

Área: Economia de Empresas

Title: Comparative Modeling Assessment of Aluminum Price Forecast

Abstract

Aluminum is one of the most important metals used by modern societies and is the most heavily traded nonferrous metal future. Price forecasting is critical for policy makers, researchers and investment decisions. Previous studies have emphasized ARIMA (Ren and Ru, 2012), structural (Ahti, 2009) or non-linear modeling (Sow, 1996) in aluminum price forecasting. This work compares out-of-sample predictive accuracy using VAR, VEC, structural and ARIMA models based on spot prices from January/1992 to April/2012. VEC has shown best forecast performance, suggesting enhanced predictability from error correction.

Resumo

Alumínio é um dos metais mais importantes utilizados pela sociedade moderna e o mais comercializado nos mercados futuros de não ferrosos. Previsão de preços é crítico para política industrial, pesquisa e decisões de investimento. Estudos anteriores têm enfatizado ARIMA (Ren e Ru, 2012), modelos estruturais (Athi, 2009) e não lineares (Sow, 2996) na modelagem de previsão de preços de alumínio. Este trabalho compara a capacidade de previsão fora da amostra de modelos VAR, VEC, estrutural e ARIMA, com base nos preços spot do metal de janeiro de 2012 a abril de 2012. VEC apresentou melhor desempenho de previsão, sugerindo melhoria de acuracidade pela introdução do fator de correção de erro.

1. INTRODUCTION

Aluminum is one of the most important metals used by modern societies. It is derived from bauxite with the intermediate stage of alumina, which is reduced into aluminum by electrolysis. It has the widest diversity of end-use applications compared to any other metal. Semi-finished steel and refined copper, for example, are both heavily reliant on the construction sector. The diversity of aluminum applications lends itself to a stronger demand performance for the light metal against other metals as it will benefit more strongly from consumer led demand once investment demand falls in the emerging markets.

Due to its light weight and electrical conductivity, aluminum wire is used for long distance transmission of electricity. Aluminum's strength, light weight, and workability have led to increased use in transportation systems including light vehicles, railcars, and aircraft as efforts to reduce fuel consumption have increased. Aluminum's excellent thermal properties and resistance to corrosion have led to its use in air conditioning, refrigeration, and heat exchange systems. Finally, its malleability has allowed it to be rolled and formed into very thin sheets used in a variety of packaging.

Aluminum global production increased by 6.5% to 44.6 million tons in 2011 compared to 41.9 million tons in 2010, according to the World Bureau of Metal Statistics. China was the largest producer and accounted for 40% of world's production in 2011, followed by Russia, Canada, the United States, Australia, India and Brazil. Demand increased by 5.5% to 42.4 million tons in 2011 compared to the previous year. Asia continues to lead world's consumption, ahead of Europe, America, Africa and Oceania.

Brazil is a key player in the global aluminum industry. In the world, Brazil is the third largest bauxite producer (only surpassed by Australia and China), the second largest alumina producer (after China and Australia) and the seventh largest aluminum producer, as indicated above. According to Brazil's Aluminum Association, aluminum industry revenues totaled US$ 18.4 billion in 2011, 25% up in 2011 compared to 2010, and accounted for 3.2% of Brazil's GDP. The industry invested US$ 1.8 billion and domestic consumption contributed to this performance, totaling 1.5 million tons in 2011, up 8.2% compared to 2010.

Aluminum contracts, denominated in US dollars, have been traded on the LME London Metals Exchange since late 1979. The LME it is the largest pure commodity exchange in Europe and the world's tenth largest futures exchange. Trading features all of the important metals commodities: aluminum, copper, nickel, zinc, lead, tin and silver. According to Watkins and McAleer (2004), the LME is used worldwide by producers and consumers as a center for spot, futures and options trading in non-ferrous metals. They indicate that the LME offers three primary functions. Firstly, market participants can hedge against the risk of price volatility. Secondly, the LME settlement prices are used as reference prices around the world. Thirdly, the LME offers the services of a global warehouse network for settlements resulting in physical delivery. Price quotes are used as reference prices in base metals trading outside of the exchange and are reported in major financial dailies.

Aluminum is the most heavily traded nonferrous metal on the LME that sets its spot and futures prices. The spot price is highly volatile, with the standard deviation of annual differences in the logarithm of the price equal to approximately 0.28 over the last three decades (Baldursson, 1999). Slow demand growth in China and economic woes in Europe weighed on market sentiment and kept investors on the sidelines. This has led to a lacklustre performance in the aluminum cash price, which averaged $2,049/t in 2012, a 15% fall on the prior year.

The sharp decline in the price was not unique to the light metal alone, as it was broadly observed across most LME traded metals. Whilst the initial downward move at the end of February 2013 was triggered by a falling Brent crude price and a strengthening US dollar, a succession of price declines resulted in the breaching of key technical levels. This prompted short-term horizon speculative traders to introduce new short positions, culminating in further price falls.

1.1 Justifications for the research

As aluminum is a key input for a variety of industrial applications, large swings in aluminum prices can have a large impact on the terms of trade. Corporate managers and policymakers, therefore, closely track changes in aluminum prices. Moreover, researchers spend much effort to forecast future price trends. Therefore, aluminum price forecasting is critical for policy makers, researchers and investment decisions.

However, to the best of our knowledge, previous studies have used ARIMA, structural or non-linear modeling, without examining comparative forecast accuracy of multivariate VAR and VEC models with traditional approaches for aluminum prices (Ren and Ru (2012), Ahti (2009), Sow (1996)). This work compares out-of-sample predictive accuracy using ARIMA, VAR, VEC and structural models based on cash prices from January/1992 to April/2012. This paper is structured as follows: in section 2 includes literature review commodity price forecasting, with focus on aluminum; section 3 covers methodology and data; section 4 shows results and discussion, and section 5 provides concluding remarks.

2 LITERATURE REVIEW

There is no doubt that commodity modeling has evolved from agricultural economics (Labys, 2006). In the beginning of the 20th century, Lehfeld (1914) used regression methods to analyze relationships between demand and prices of agricultural commodities.

Classical commodity forecasting aims at predicting both the level and turning point of prices. The most basic commodity model from which econometric and modeling methodologies have developed is the competitive market model. This model neglects market imperfections and assumes that supply and demand interact to produce an equilibrium price. Such model can be expressed as some regression equations relating supply, demand, prices and inventories. Despite simplifying assumptions, a major utility stems from providing a framework for capacity expansion, impacts on regulatory policies and price behavior. Such model specifications appear back in Labys (1973) and in Lord (1991).

This approach considers expectations from buyers and sellers concerning commodity prices. These goods are traded using formal contract terms, such as maturity, volume and prices. In spot contracts, buyers and sellers close their positions immediately. As to futures contracts, positions are closed with a specific future contract terms and expectations from participants are based on the variance between spot and future prices.

The market expectation hypothesis is based on risk neutral economic agents, zero costs transactions, rationality and competitive markets; with these aspects the market will be efficient and so the expected rate of return in the future market would be zero. According to Otto (2011), these markets are based on the coexistence of spot and future contracts.

Hansen and Hodrick (1980) and King (2001) presented formally the market efficiency. According to them, the forecast error is $et = S(t+s) - Ft$ with zero mean and serially uncorrelated. Thus, the future price (Ft) would be assumed as the best unbiased predictor of the future spot price ($S(t+s)$) under such conditions.

One of the first works suitable for analyzing mineral markets using such competitive market approach was developed by Desai (1996), covering a tin model that explained tin fluctuations on a world basis. Fisher et al. (1972) built a world copper model to include long run adjustments, combined with a short term inventory adjustment process.

In 1981, Hojman developed a model of the international bauxite-aluminum economy for the analysis of bauxite carted pricing. The model assumed bauxite production dependent on aluminum price, and an aggregate output or income variable. Relations between both these variables and production were positive. In a longer-term perspective, it was indicated that cartel would be condemned to attending a residual market. Income elasticities were found to be high, while price and substitution elasticities were low.

Fisher and Owen (1981) developed an economic model of the US aluminum market using annual data from 1960-78. The results of the estimation indicated that demand was generally insensitive to changes in price, and highly dependent upon aluminum end-use activity while price elasticities were low for both short and long term.

Bird (1993) examined some of the data from the 1982-92 period so as to draw lessons from a ten-year history of changing production cost patterns. Results showed that the average cost of producing aluminum fell slightly in nominal terms between 1982-92, but there was a sharp fall in real terms. The average cost also showed a marked cyclical fluctuation, partly as a result of the feedback effect from aluminum prices to production costs. Between 1985 and 1992, exchange rate fluctuations produced a sharp change in the relative position of US and European smelters.

Gilbert (1995) developed a model in which the dual price formation and stockholding equations were jointly estimated subject to a large number of inter- and intra-equation restrictions. He showed that the competitive model requires that, in the aluminum market, the supply-demand balance be augmented by a second state variable given by the difference between production and trend consumption demand, interpreted as long term excess supply.

Sow (1996) presented a study to assess the scarcity of nonrenewable natural resources, including aluminum, copper, lead, zinc, tin, molybdenum, stel, oil, and coal. Multivariate state space and learning model methods were used to project real prices of mineral resource products to the year 2011. The study found that all commodities prices are either declining or flat, thus indicating a general failure to support a claim of increasing scarcity of mineral resources. However, observation of the entire price series for some commodities reveals increasing trends in prices, and thus increasing economic scarcity.

Baldursson (1999) formulated a partial equilibrium model of an industry which produced a storable primary commodity under uncertain demand. He showed that in a competitive model of production and inventory speculation it is entirely rational, when adjustment costs are linear, for producers to be slow in adjusting their output to changes in price. The primary reason is the option value of waiting which is usually omitted in conventional analysis of market balance. Thus, a large portion of the industry may continue production while being far from covering their variable costs. It is only when prices fall considerably below variable costs, in the order of 20 to 30% with typical parameter values, that it is rational to exercise the option of exit. At that point exit may happen quite fast and further price falls will be prevented.

Ferretti and Gilbert (2001) examined the impact of the pricing regime on price variability with reference to the non-ferrous metals industry. Theoretical arguments are ambiguous, but suggest that the extent of monopoly power is more important than the pricing regime as a determinant of variability. It is likely that price variability imposes costs on metals consumers and it is widely supposed that the move from producer pricing to exchange-based pricing has resulted in an increase in metals price variability.

Ferretti (2003) developed a work to reflect structural changes that have characterized the aluminum industry over the last few decades. In order to capture the changes in competition, the author estimated cost and related it to output prices by illustrating the effect of the prevalent industry risk sharing agreements. This work argued that, contrary to what the microeconomic paradigm envisages, in the short run prices mainly determine costs as the consequence of a an exchange pricing system involving contractual risk-sharing arrangements. Costs determine prices only in the long run through investment in new smelting capacity.

Ferretti and Gilbert (2005) made an attempt to quantify the relative information content of the different exchange and non-exchange pricing regimes that have been prevalent in the aluminum industry. Specific attention was paid to U.S. producer prices until their abandonment in the mid-1980s, transactions prices published in a trade journal (the *Metal Bulletin*, MB), and LME and Comex exchange prices over the periods which they were traded. These estimates show that the information content of the Metal Bulletin transactions price increased once futures trading started, although the LME price was the more informative of the two prices.

Ferretti (2008) analyzed a dynamic representation of spot and three-month aluminum and copper volatilities, using a bivariate FIGARCH model. The results showed that spot and three-month aluminum and copper volatilities follow long memory processes, that they exhibit a common degree of fractional integration and that the processes are symmetric. However, there is no evidence that the processes are fractionally cointegrated. This high degree of commonality may result from the common LME trading process.

Athi (2009) developed STAR and artificial neural network nonlinear forecasting price models for metals traded on the LME from 1970-2009 and compared with ARMA and random walk models. Out-of-sample results indicate that, with respect to weekly and monthly data, nonlinear models produce the lowest forecast errors. However, in some cases the Diebold-Mariano tests cast doubt on whether the observed differences in forecast performance between nonlinear and linear models are statistically significant.

Ferretti and Gonzalo (2010) presented an equilibrium model of commodity spot and futures prices, with finite elasticity of arbitrage services and convenience yields. By explicitly incorporating and modelling endogenously the convenience yield, their theoretical model was able to capture the existence of backwardation (when future prices are lower than spot prices) or contango (when future prices are higher than spot prices) in the long-run spot-futures equilibrium relationship.

Ru and Ren (2012) developed traditional ARMA model for aluminum price forecasting, but no comparison was made with benchmark or more advanced models and only 8 sample data was used for forecast accuracy testing. Price data was obtained from the Yangtze River non-ferrous spot market from January 4, 2006 to August 31, 2011, sampled for weekly average price.

Pierdzioch, Rülke and Stadtmann (2013) analyzed monthly survey data of price forecasts for nine metals compiled by Consensus Economics Forecast for the time period 1995–2011. Consensus Economics is a leading international economic survey organization and polls more than 700 economists each month to obtain their forecasts and views. The main finding is that forecasters appear to anti-herd, where the prevalence of forecaster anti-herding has undergone changes over time. Findings suggest that forecaster anti-herding is a source of the empirically observed cross-sectional heterogeneity of forecasts. As a result, forecasts of metal prices give, for an outside observer, a more dispersed and, thus, less precise account of expected future movements of metal prices than it would be the case if private sector forecasters delivered unbiased forecasts

Although VAR models have been used primarily for macroeconomic models, they offer an interesting alternative to structural or ARIMA models for problems in which simultaneous forecasts are required (Ramos, 2003). This would be the case for aluminum industry spot and forward prices The use of VAR models for economic forecasting was proposed by Sims (1980), motivated partly by questions related to the validity of the way in which economic theory is used to provide a priori justification for the inclusion of a restricted subset of variables in the 'structural' specification of each dependent variable. Such time series models have the appealing property that, in order to forecast the endogenous variables in the system, the modeller is not required to provide forecasts of exogenous explanatory variables; the explanatory variables in an econometric model are usually no less difficult to forecast than the dependent variables. In addition, the time series models are less costly to construct and to estimate. Concerning VEC models, if each element of a vector of time series x(t) first achieves stationarity after differencing, but a linear combination v.x(t) is already stationary, x(t) is said to be co-integrated with vector v (Engle and Granger, 1987). Co-integration implies that deviations from equilibrium are stationary, with finite variance and thus they have a long term relationship.

From the above mentioned literature, only the studies by Sow (1996), Athi (2009) and Ru and Ren (2012) were primarily focused on aluminum price forecasting. However, to the best of our knowledge, comparison of multivariate VAR and VEC with structural and traditional model has not been assessed for aluminum price forecasting. The present work contributes to the literature by comparing out-of-sample predictive accuracy using VAR, VEC, structural and ARIMA models based on spot prices from January/1992 to April/2012

3 METHODOLOGY

3.1 Data

It was used a theoretical and empirical approach, based on a sample of LME daily spot and 3 month prices that were averaged to obtain monthly data from January 1992 to April 2012. Model estimation was based on data from January 1992 to April 2012, while out-of-sample forecast performance used 24 data points, from May 2010 to April 2012. According to Otto (2011), LME forward contracts that present better liquidity are the 3 month contracts, traded on a daily basis for a consecutive period of 3 months.

Aluminum price series is indicated in Figure 1, where it is observed a peak of US$ 3,645/t in June 1988. Between 1990 and 2005, prices have fluctuated around US$ 1,500/t, noting a significant price increase until mid-2008, mainly driven from China demand. Price decrease from US$ 3,071/t in July 2008 to US$ 1,330 in February 2009 is explained by the 2008/09 global finance crisis. Price recovery is observed until the first quarter of 2011, when Eurozone crisis effects, coupled with lower China growth (around 8%-9% compared to a rate above 10% in prior years) have led to a new price decline on a level that stands at US$ 2,000/t.

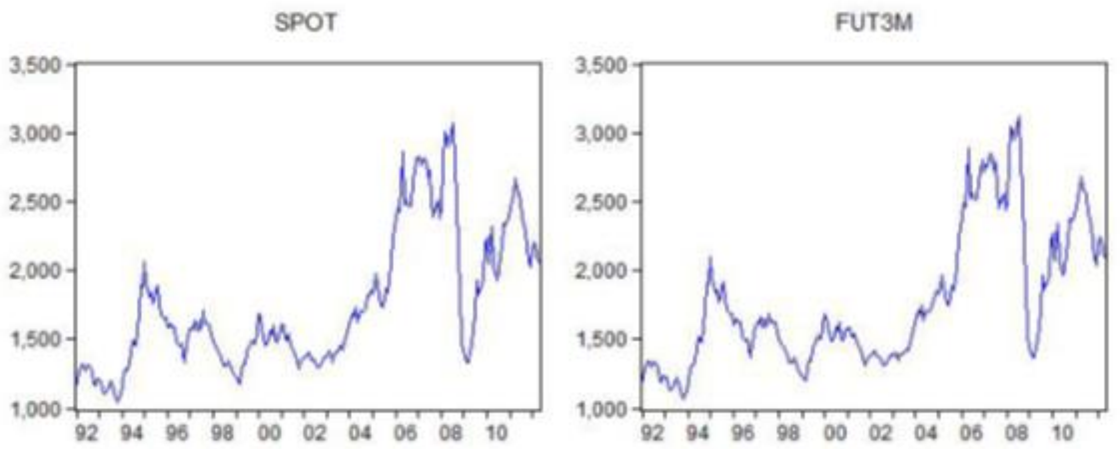

Figure 1: Spot and 3 month forward aluminum prices

3.2 Models

3.2.1 Autoregressive Integrated Moving Average Models (ARIMA)

According to Box and Jenkins (1970) approach, if a stochastic process y(t) is not stationary, but becomes stationary after "d" differences, it is referenced as an ARMA(p,q) process, while the time serie y(t) is an ARIMA(p,d,q) process. Thus, the Box-Jenkins procedure is called ARIMA forecast; this methodology includes four steps: identification, estimation, verification and forecast.

The identification step occurs through the analysis from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), equations (1) and (2), respectively. Such functions drive the choice of the AR(p) and MA(q) order.

$$r_k = \frac{\sum_{t=1}^{T} (y_t - \bar{y})(y_{t-1} - \bar{y})}{\sum_{t=1}^{T} (y_t - \bar{y})^2} \tag{1}$$

$$\rho_k = \beta_k \text{ na regressão } y_t = \beta_1 y_{t-1} + \cdots + \beta_k y_{t-k} + \epsilon_t \tag{2}$$

The estimation step is realized by Conditional Least Squares, Maximum Likelihood or Nonlinear Least Square in the stationary (3).

$$\begin{aligned} y_t - \theta_1 y_{t-1} - \ldots - \theta_p y_{t-p} &= \epsilon_t + \alpha_1 \epsilon_{t-1} + \ldots + \alpha_q \epsilon_{t-q} \\ \theta(L) y_t &= \alpha(L) \epsilon_t \end{aligned} \tag{3}$$

The verification and forecast are made by observation of the stationarity and invertibility condictions. After that, the information's criteria (Akaike, Schwarz and Hannan-Quin) and RMSE, MAE and MAPE index are observed.

3.2.3 Vector Autoregressive (VAR) and Vector Error Correction (VEC)

The Vector Autoregressive and the Vector Error Correction are estimated by equations (4) and (5).

$$\Delta y_t = \alpha + \sum_{i=1}^{n} \beta_i \Delta x_{t-i} + \sum_{i=1}^{n} \gamma_i \Delta y_{t-i} + \epsilon_t \tag{4}$$

$$\Delta y_t = \alpha + a(TCE_{t-1}) + \sum_{i=1}^{n} \beta_i \Delta x_{t-i} + \sum_{i=1}^{n} \gamma_i \Delta y_{t-i} + \epsilon_t \tag{5}$$

In the equation (5), "*a*" is the speed of adjustment and TCE is the Term of Error Correction; these parameters are estimated by Johansen (1988) procedure, the cointegration analysis between spot and future prices. The orders of models (4) and (5) are selected by the information's criteria (Akaike, Schwarz and Hannan-Quin) and the FPE (Final Prediction Error) values; after the estimation the error autocorrelations (Portmanteau and LM tests) and normality (Doornik and Hansen (1994) and Urzúa (1996)) are evaluated.

3.2.4 Structural Model

The basic structural model is presented by system into (6); Harvey (1988) showed that structural models are an alternative for the ARIMA models when there are problems. For example, the identification processes in small samples are weak because the ACF and PACF present weak results in these situations.

$$\begin{aligned} y_t &= \mu_t + \gamma_t + \epsilon_t \\ \mu_t &= \mu_{t-1} + \beta_t + \eta_t \\ \beta_t &= \beta_{t-1} + \zeta_t \\ \gamma_t &= -\sum_{i=1}^{s-1} \gamma_{t-i} + \omega_t \end{aligned} \tag{6}$$

In (6), $\mu(t)$ is the trend component, $\beta(t)$ is the level component, $\gamma(t)$ is the seasonal component and $\varepsilon(t)$, $\eta(t)$, $\zeta(t)$ and $\omega(t)$ are white noise components. The parameters are achieved applying the maximization of a recursive Likelihood function through the use of the Kalman filter.

4 RESULTS AND ANALYSIS

4.1 Unit Root Tests

Regarding unit root tests, the Dickey and Pantulla (1987) procedure was selected to evaluate if there were 2 unit roots or 1 unit root in the time series (Table 1). The Augmented D-F test (DICKEY; FULLER, 1981) and KPSS test (KWIATKOWSKI *et al*, 1992) were evaluated to detect existence of 1 unit root or 0 unit root. In general, all tests showed 1 unit root for the level and 0 unit root (stationary) for the first differences.

Table 1:
Dickey and Pantulla unit root test

Hypothesis	**P(0.9)**	**P(0.95)**	**P(0.99)**	**t(spot)**	**Decision**
H0: Trend = 0	2.38	2.79	3.49	-0.50	Do not reject
H0: Constant = 0	2.16	2.53	3.19	0.75	Do not reject
H0: 2 root units	-1.62	-1.94	-2.57	-4.18	Reject

4.2 Models

The models were estimated after unit root tests for spot price forecasting. The ARIMA and VAR models were analyzed in the series with first difference applied. The VEC and Structural models were analyzed in the level of the series.

4.2.1 Autoregressive Integrated Moving Average Models (ARIMA)

The identification process was realized through the ACF and PACF, the models selected were ARIMA(1,1,0); ARIMA(0,1,2); ARIMA(10,1,0); ARIMA(20,1,0); ARIMA(20,1,1); ARIMA(1,1,2); ARIMA(1,1,20). In the verification process was observed the stationary and invertibility hypothesis, the information criteria values and the residual autocorrelations.

The models selected for the forecast step were ARIMA(20,1,0); ARIMA(20,1,1) and ARIMA(1,1,20). After the analysis of RMSE, MAE and MAPE index, the final model selected was the ARIMA(20,1,0); a summary of results is presented in Table 2.

Table 2:
ARIMA results

Models	**Sta./Inv.**	**Akaike**	**Schwarz**	**HQ**	**Autoc.**	**Sig.**	**RMSE**
ARIMA(1,1,0)	**Yes**	-3,2246	**-3,1936**	**-3,2121**	problem aut.	ar(1)	-
ARIMA(0,1,2)	**Yes**	-3,2119	-3,1645	-3,1922	problem aut.	ma(1), ma(2)	-
ARIMA(10,1,0)	**Yes**	-3,2222	**-3,1745**	-3,2031	problem aut.	ar(1), ar(10)	-
ARIMA(20,1,0)	**Yes**	**-3,2498**	-3,167	**-3,2163**	**no aut.**	ar(1), ar(10), ar(19), ar(20)	**0,052378**
ARIMA(20,1,1)	**Yes**	**-3,2412**	-3,1419	-3,201	**no aut.**	ar(1), ar(10), ar(19), ar(20)	0,052383
ARIMA(1,1,2)	**Yes**	-3,2131	-3,151	-3,188	problem aut.	ar(1)	-
ARIMA(1,1,20)	No	**-3,3324**	**-3,2393**	**-3,2948**	**no aut.**	ar(1), ma(1), ma(10), ma(19)	-

4.2.3 Vector Autoregressive (VAR) and Vector Error Correction (VEC)

The estimation for the VAR and VEC models started by order selection, information criteria (Akaike, Schwarz, Hannan-Quin) and FPE. For VAR model 2 lags were selected and for VEC model, 3 lags. Only 1 equation was estimated for VAR model, but 3 equations was analyzed for VEC model; VEC 1 – no tendency and no constant in cointegration equation (CE); VEC 2 – no tendency with intercept in CE; VEC 3 – tendency and intercept in CE.
The autocorrelation of residuals from the models were analyzed, but no problems were observed. In the finish, the VEC models were compared and VEC 1 was selected (Table 3).
The variables spot (*Lspot*) and future (*Lfut3m*) log price were utilized.

Table 3:
VEC models results

Model	RMSE	MAE	MAPE
VEC 1	0,04693	0,03534	0,7344%
VEC 2	0,04688	0,03537	0,7350%
VEC 3	0,04726	0,03554	0,7387%

4.2.4 Structural Model

For structural model estimation, the objective is to search a model with smaller Prediction Error Variance (P.E.V.); also, the models are restricted by no residual autocorrelation and normality. Two models were analyzed and two steps were realized for search by smaller P.E.V.

In the first model analyzed was utilized the log spot price (*Lspot*); in the first step was searched and selected for a second step models with less P.E.V. In the second step was tried to correct the problems in the first step, but these problems weren't corrected. Thus, a second model was verified.

The second model was estimated with the log spot price as dependent variable and the log spot price with 1 lag (*Lspot(-1)*) as independent variable. Again, in the first step was searched and selected for a second step models with less P.E.V; the second step is detailed in the Table 4

Table 4:
Structural models results *Lspot(-1)*

Model	Level	Slope	Irregular	Seasonal	Autoreg.	Intervention	P.E.V.
1	stochastic	stochastic	yes	fixed	no	lvl 2008.12	0,001973
2	stochastic	fixed	yes	fixed	no	lvl 2008.12	0,001973
3	stochastic	fixed	no	fixed	yes	lvl 2008.12	0,001973
4	stochastic	fixed	yes	fixed	no	lvl 2008.10, 2008.12	0,001835
5	stochastic	fixed	no	fixed	yes	lvl 2008.10, 2008.12	0,001833
6*	**stochastic**	**fixed**	**yes**	**fixed**	**no**	**irr 2006.5, lvl 2008.10, 2008.12**	**0,001733**

*Model selected for forecast.

The predictive capacity was observed by "Failure test" and "Cusum", the null hypothesis is "the prevision was successful". The results showed that there are evidences for don't reject the null hypothesis (Failure test: *25,92 (p=0,36)*) .

4.3 Discussion

Estimation equations for VEC, VAR and ARIMA models are indicated in (7), (8), and (9), respectively. For the structural model, that uses recursive estimation based on Kalman filter, final state vector and variables are represented in Table 5.

Out-of-sample forecast accuracy testing covered the period from May 2010 to April 2012. Forecast evaluation comparison was determined by computing the root mean squared error (RMSE), mean average error (MAE) and mean average percentage error (MAPE), indicated in Table 6.

$$\begin{cases} \Delta lspot_t - 0{,}3(TCE_{t-1}) - 0{,}02\Delta lspot_{t-1} - 0{,}07\Delta lspot_{t-2} \\ \quad +0{,}33\Delta lfut3m_{t-1} - 0{,}04\Delta lfut3m_{t-2} \\ \quad TCE_{t-1} = lspot_{t-1} - 0{,}99 lfut3m_{t-1} \end{cases} \tag{7}$$

$$\Delta lspot_t = -0{,}16\Delta lspot_{t-1} - 0{,}05\Delta lspot_{t-2} + 0{,}46\Delta lfut3m_{t-1} + 0{,}09\Delta lfut3m_{t-2} \quad (8)$$

$$\Delta lspot_t = 0{,}25AR(1) - 0{,}24AR(10) - 0{,}19AR(19) - 0{,}19AR(20) \quad (9)$$

Table 5:
Final state vector Structural model

Variables	Coef.	Explanatory variables	Coef
Lvl	4,7304	lspott-1	0,3902
Slp	0,0034	Irr 2006.5	0,1233
Sea1	0,0123	Lvl 2008.10	-0,1766
Sea2	0,0049	Lvl 2008.12	-0,1975
Sea3	0,0043		
Sea4	-0,0044		
Sea5	-0,01		
Sea6	0,0132		
Sea7	-0,0016		
Sea8	-0,0201		
Sea9	-0,018		
Sea10	-0,0064		
Sea11	0,0078		

Table 6:
Forecast accuracy comparsion

Model*	**RMSE**	**MAE**	**MAPE**
VEC1	0,0469	**0,0353**	**0,7344%**
VAR	**0,0468**	0,0354	0,7359%
ARIMA	0,0524	0,0365	0,7576%
Structural	0,0464	0,0377	0,7835%

*Best values in bold

As indicated above, VEC provided the best forecast accuracy performance compared according to both MAE and MAPE criteria. VAR was the second best model and delivered the lowest RMSE. It is worthwhile to mention that these estimates are valid only for the out-of-sample analyzed period. Additional estimates would be necessary to assess model predictability in other sub-set of forecasting periods. This result suggests that the use of lags and error correction term contributed to improved predictability for the VEC model. Figure 2 below indicates comparison between actual and forecast prices according to the VEC model.

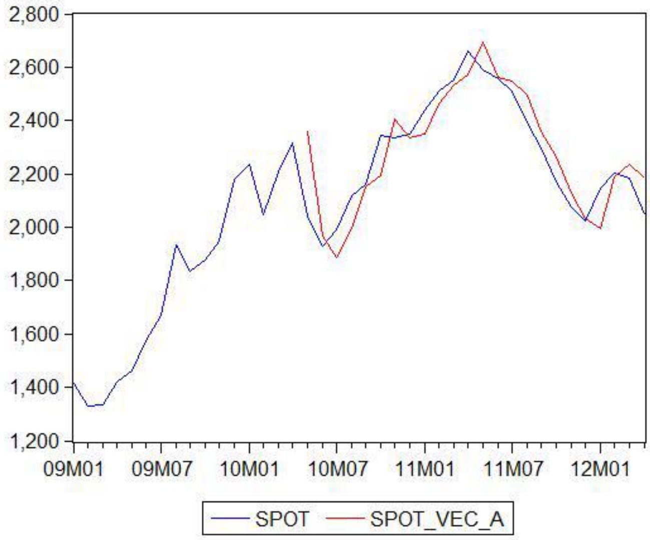

Figure 2: Comparative performance between actual data and VEC forecasts

5 CONCLUSIONS

As aluminum is a key input for a variety of industrial applications, large swings in aluminum prices can have a large impact on the terms of trade. Corporate managers and policymakers, therefore, closely track changes in aluminum prices. Moreover, researchers spend much effort to forecast future price trends. Therefore, aluminum price forecasting is critical for policy makers, researchers and investment decisions.

Previous studies have used ARIMA, structural or non-linear modeling, without examining comparative forecast accuracy of multivariate VAR and VEC models with traditional approaches for aluminum prices (Ren and Ru (2012), Ahti (2009), Sow (1996)). This work compares out-of-sample predictive accuracy using ARIMA, VAR, VEC and structural models based on cash prices from January/1992 to April/2012.

VEC provided the best forecast accuracy performance according to both MAE and MAPE criteria. VAR was the second best model and delivered the lowest RMSE. It is worthwhile to mention that these estimates are valid only for the out-of-sample analyzed period. Additional estimates would be necessary to assess model predictability in other sub-set of forecasting periods. This result suggests that the use of lags and error correction term contributed to improved predictability for the VEC model. Future research would involve the use of forecasting models for conditional volatility as daily aluminum price series may present heteroscedasticity periods.

REFERENCES

ATHI, V. *Forecasting Commodity Prices with Nonlinear Models*. Discussion Paper n. 268, ***Helsinki Center of Economic Research***, ISSN 1795-0562, July 2009

BALDURSSON, F. *Modeling the Price of Industrial Commodities*, ***Economic Modeling,*** v.16, p. 331-353, 1999

BIRD, A. *Changing Patterns in Aluminium Production Costs*. ***Natural Resources Forum***, v5, p. 151-155, 1993

BOX, G.; JENKINS, G. ***Time series analysis: Forecasting and control***. San Francisco: Holden-Day, 1970.

CASTRO, J. B. B.; MONTINI, A. A. Análise comparativa de modelos de previsão: Aplicação do Model Confidence Set para preços de alumínio. In: SEMINÁRIOS EM ADMINISTRAÇÃO - SEMEAD, 15., 2012, São Paulo. **Anais.** São Paulo: SEMEAD, 2012.

DESAI, M. *An Econometric Model of the World Tin Economy*. ***Econometrica***, v. 34, p. 105-134, 1996

DICKEY, D. A.; FULLER, W. A. *Likelihood ratio statistics for autoregressive time series with a unit root*. ***Econometrica: Journal of the Econometric Society***, v. 49, n. 4, p. 1057-1072, 1981.

DICKEY, D. A.; PANTULLA, S. *Determining the order of di_erencing in autoregressive processes*. ***Journal of Business & Economic Statistics***, v. 5, n. 4, p. 455-461, 1987.

DOORNIK, J. A.; HANSEN, H. A practical test for univariate and multivariate normality. [S.l.], 1994.

ENGLE, R., GRANGER, C. *Co-Integration and Error Correction: Representation, Estimation and Testing*. ***Econometrica***, v. 55, n.2, p. 251-276, 1987

FERRETTI, I., GILBERT, C. *Price Variability and Marketing Method in Non-ferrous Metals*. ***Resources Policy***, v. 27, p. 169-177, 2001

FERRETTI, I. P*rices and Production Cost in Aluminium Smelting in the Short and Long Run*, ***Working Paper 03-39, Universidad Carlos III***, Madrid, 2003

FERRETTI, I., GILBERT, C. *Price Discovery in the Aluminum Market*. ***The Journal of the Futures Markets***, v. 25, p. 967-988, 2005

FERRETTI, I. *Commonality in the LME Aluminum and Copper Volatility Processes Through a FIGARCH Lens*, ***The Journal of the Futures Markets***, v. 28, p. 935-962, 2008

FERRETTI, I., GONZALO, J. *Modelling and Measuring Price Discovery in Commodity Markets*. ***Journal of Econometrics,*** v. 158, p. 95-107, 2010

FISCHER, F., COOTNER, P., BAILEY, M. *An Econometric Model of the World Copper Industry*. ***Bell Journal of Economics***, v. 3, p. 568-609, 1972

FISCHER, L., OWEN, A. *An Economic Model of the US Aluminum Market*. ***Resources Policy***, v. 6, p. 151-160, 1981

GILBERT, C. *Modelling Market Fundamentals: A Model of the Aluminium Market*, ***Journal of Applied Econometrics***, v. 10, n.4, p. 385-410, 1995

HANSEN, L.P.; HODRICK, R. J. *Forward Exchange Rates as optimal Predictors of Spot Rates: An Econometric Analysis*. ***Journal of Political Economy***, Vol. 88, pp. 829-853, 1980.

HARVEY, A. C. ***Forecasting, structural time series models and the Kalman Fillter***. Cambridge: Cambridge university press, 1989.

HOJMAN, D. *An Econometric Model of the International Bauxite-Aluminum Industry*. ***Resources Policy***, v.6 , p. 87-102, 1981

JOHANSEN, S. *Statistical analysis of cointegration vectors*. ***Journal of Economic Dynamics and Control***, Elsevier, v. 12, n. 2, p. 231-254, 1988.

KING, J. *Testing the Efficient Markets Hypothesis with Futures Markets Data: Forecast Errors, Model Predictions and Live Cattle*. ***Australian Economic Papers***, Vol. 40, pp. 581-585, 2001.

LABYS, W. ***Modeling and Forecasting Primary Commodity Prices***. Hampshire: Ashgate, 2006

LABYS, W. ***Dynamic Commodity Markets: Specification, Estimation and Simulation***. Lexington: Heath, 1973

LEHFELDT, R. *The Elasticity of Demand for Wheat*. ***Economic Journal***, v. 24, p. 212-217, 1914

LORD, M. ***Imperfect Competition and International Commodity Trade***. Clarendon: Oxford, 1991

OTTO, S. *A Speculative Efficiency Analysis of the London Metal Exchange in a Multicontract Framework*. ***International Journal of Economics and Finance, Canadian Center of Science and Education***, v. 3, n. 1, p. 3-16, 2011.

PIERDZIOCH, C., RULKE, J., STADTMANN, G. *Forecasting Metal Prices: Do Forecasters Herd?* ***Journal of Banking and Finance***, v. 37, p. 150-158, 2013

RAMOS, F. *Forecasts of market shares from VAR and BVAR Models*, ***International Journal of Forecasting***, v. 19, p. 95–110, 2003

RU, Y., REN, H. *Application of ARMA Model in Forecasting Aluminum Price*, ***Applied Mechanics and Materials***, v. 155, p. 66-71, 2012

SIMS, C. *Macroeconomics and Reality*. ***Econometrica***, v. 48, p.1-48, 1980

SOW, T. *Multivariate Forecasting of Mineral Commodities Prices: Implications for Natural Resource Scarcity*, ***PhD Dissertation, University of Arizona***, 1996

URZÚA, C. M. *On the correct use of omnibus tests for normality*. ***Economics Letters***, Elsevier, v. 53, n. 3, p. 247-251, 1996.