The International Journal of Business Management and Technology, Volume 4 Issue 5 September–October 2020
ISSN: 2581-3889

Research Article Open Access

Forecasting Steel Prices Using ARIMAX Model: A Case Study of Turkey

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Abstract: Steel prices for Turkey as a major steel producer and exporter have substantial importance to be predicted. The *ARIMA* model with explanatory variables is used to assess the out-of-sample forecast accuracy with the univariate *ARIMA* as a benchmark. The results revealed that despite expectations, The *ARIMA* model with explanatory variables could not perform superior results comparing *ARIMA* models in a 6-month forecast horizon.

Keywords: ARIMA, ARIMAX, Forecast, Steel Prices

I. Introduction

Steel is an essential base metal that forms the spine of the industry. The price of steel products has been a vital issue for policymakers in the country or corporate level. Hence, the prediction of the steel prices is highly in demand for various establishments. The steel prices became more volatile due to globalization and consequently by trading as a financial tool in commodity exchange markets. Thus, the prediction of steel prices has significant effects on the decision-making process at all levels to handle the risk of changing prices.

The steel price prediction has a substantial role in developing countries, especially the ones who are the producers of steel products. whereas they consume steel as a manufacturing or construction raw material, or it has a significant proportion in their export basket.

Turkey as a significant producer and exporter of steel, is included among the top 10 producers of crude steel as the eighth rank both in 2017 and 2018 with 37.5 and 37.3 million tons, respectively (Worldsteel Association, 2019). In 2018 foreign trade data, Turkey ranked as an exporter of steel products in sixth place and 10th in imports of steel with 19.7 and 12 million tones (ITA, 2019). From the Turkish economy perspective, steel industry exports are %10.5 of total export value, with 17.7 billion USD revenue in 2018. Also, in 2017, some 88,217 direct employees had been working in the steel industry, according to the productivity general directorate of the ministry of industry and technology of Turkey. Turkey is the largest importer of scrap steel in the world, which is used to produce steel products as well as iron ore.

Assessing Turkey's steel industry, The Erdemir is the largest producer of steel products while had 47th place in the world, in 2018, with 9. million tons of crude steel production following by 5.6 million USD sales revenue. The employee numbers were 11,428 people in 2019 (ERDEMIR, 2019).

Due to unbalanced production between long and flat products, Turkey relies on imports of flat products for satisfying its increasing domestic demand along with investing in flat products making capacity. Therefore, steel making companies and governments must determine and predict flat steel prices to have a clear vision about costs and future plans that yet has to come.

The majority of studies in the literature have tried to determine the steel industry in various regions. Therefore, few of them attempted to forecast steel prices. Blecker (1989), Blonigen, Liebman, & Wilson (2007), Grossman (1986), Liebman (2006) and, Mancke (1968) have studied the United States steel industry and investigate the effects of tariffs and imports to domestic steel prices by using classic multiple regression analysis.

Richardson (1999) assessed the impact of low price steel products import from the eastern European countries into the European Union using regression analysis. As a comprehensive perspective, Malanichev & Vorobyev (2011) formed a multiple regression model to forecast steel prices globally. For input variables, the used raw materials for steel making and capacity utilization for the steel industry. Kahraman & Unal (2012) and Wu & Zhu (2012) utilized univariate analysis to predict the steel prices in Turkey and China using Autoregressive and Neural Networks models, respectively.

As a new study, Liu, Wang, Zhu, & Zhang (2014) tried to predict steel prices in China with the help of multivariate Neural Networks algorithms. However, new econometric models have not been used for forecasting steel prices. Ming-Tao Chou, Ya-Ling Yang (2012) studied the relationship between crude oil prices and global steel prices and found a long-run positive relationship using Vector Autoregressive (VAR) model. Chou (2016) considered the effects of Asian, European Union, and North American steel price indexes on fright rates with the help of the VAR model. Also, Todshki & Ranjbaraki (2016) determined Iran steel import and export quantity by using macroeconomic factors by testing for cointegration between variables.

In this study, we implement the ARIMA model with explanatory variables to investigate whether it can outperform univariate ARIMA or not. for explanatory variables, we use iron ore and steel scrap as raw materials and crude Brent oil price as an energy indicator. Section 2 is donated to the methodology of the ARIMAX model, followed by section 3, which is data description and empirical results. Section 4 and 5 are discussion and conclusion parts.

II. The Methodology

2.1 ARIMA Model with Explanatory Variables

For model description, almost the same methodology is used as George Box and Jenkins (1976), which is repeated more transparent in (Rob J Hyndman & Athanasopoulos, 2018). The processes for ARIMA (p, d, q) model are constituted of the Autoregressive, the Integration order, and the moving average parts. The process that must be considered initially is I(d), which stands for the order of the integration. The order of integration defines the order of differencing to remove the unit root from a time series to become stationary. For the aim of making a time series weak stationery (stationary in mean and variance), which Box-Jenkins method needs most, in addition to differencing, we usually need to transform the series by the natural log or square root to stabilize the variance.

The *AR(p)* process refers to the Autoregressive process of order p, which delineates the relationship of the target variable with the linear combination (regression) of its past values.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \quad (1)$$

Where "ϕ" is called the autoregressive coefficient and "ε_t" is white noise.

The third process is MA(q) referring moving average process of order "q", where the variable of interest "y_t" is the function of current and several past shocks (errors).

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (2)$$

Where θ is moving average coefficient and "ε_t" is white noise.

ARIMA (Autoregressive Integrated Moving Average) model is the combination of these three processes, which usually is being shown as ARIMA (p, d, q).

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (3)$$

For parsimony purposes, the ARIMA model is written with backshift notations, where B is used as a backward shift operator. It takes effect by shifting the data one period back. Backshift notation for ARIMA (p, d, q):

$$\phi(B) y_t = c + \theta(B) \varepsilon_t \quad (4)$$

Where$(\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p)$ and, $(\theta(B) = 1 - \theta_1 B - \cdots - \theta_p B^p)$.

For the initial identification of (p, q) orders, George Box and Jenkins (1970) suggested using autocorrelation function (ACF) and partial autocorrelation function (PACF). However, this method could only be useful for some specific patterns in time series. For more rigorous recognition of (p, q) orders, Rob J Hyndman and Athanasopoulos (2018) suggested using Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) minimization, but not for (d) order. The AIC is preferable when the model is expected to be complicated and unbounded, whereas the BIC is more suitable for parsimonious models (Aho, Derryberry, & Peterson, 2014; Vrieze, 2012). As reviewed from the literature, we expect parsimonious models for our data; hence in this paper, BIC is used to choose the best model.

Usually, the estimation of ARIMA parameters (ϕ) and (θ) is through maximum likelihood although, the AR process can be estimated with the ordinary least square (OLS) method as well.

Using the ARIMA model along with explanatory variables (ARIMAX) is belongs to the class of dynamic regressions, which encompasses a wide variety of models, including classic multiple regression models where input variables have an instantaneous effect on the output variable. For representing the ARIMAX model, we use equation (4) as:

$$\phi(B)y_t = c + \beta X_t + \theta(B)\varepsilon_t (5)$$

While here, X_t is an explanatory variable at time t, It is possible to have more than one explanatory variables. Also, along with the instantaneous effect, the effect of explanatory variables on the dependent variable might be delayed for several lags in some situations.

III. Data Description and Empirical Results

3.1 Data Description

The data are monthly data from January 2013 to December 2019 for a total of 84 months. For steel prices (STP), the flat steel data are attained from a domestic company. To evaluating the influence of explanatory variables on steel prices forecasting performance, variables are used as:

The producer Price Index for Ferrous Metal Scrap (SCP) (U.S. Bureau of Labor Statistics, 2020) is used as raw material to produce steel products. The global price of Iron Ore (ORP) ($/ton) (International Monetary Fund, 2020b) is a primary raw material in the steel making process. The global price of Brent Crude Oil (OIP) ($/Barrel) (International Monetary Fund, 2020a) as a representative for energy prices. All data are indexed as January 2013=100. For stabilizing the variance and reduce the effects of interventions, natural logarithm transformation is applied to all variables. This paper aims to perform an out-of-sample forecast for multiple steps ahead (6 periods) using ARIMA and ARIMAX models. While usually, in-sample forecasts result in a better model fit; however, they can become over-fitted, and in practice, they will not be useful. Thus, the Out-of-sample forecast is used to evaluate the fitted model to assess the generalizability of our models. Data from January 2013 to June 2019 (78 months) are used for a model estimation, which then data from July 2019 to December 2019 (6 months) are used for model validation.

3.2 Empirical Results

Initially, in modeling with the ARIMA process, we need to assess series for stationarity conditions. For this reason, the augmented-dickey fuller test (ADF), which is introduced by Dickey & Fuller (1979), is used in this paper.

The null hypothesis (H_0), for the ADF test, suggests that there is a unit root in data, and thus it is non-stationary. The alternate hypothesis (H_a), has different variations. With the ADF test is applied to the original series reveals that there is a non-stationarity in the data since the p-value is insignificant; hence the null hypothesis cannot be rejected. However, after Natural logarithm transformation and first differencing, the result of the test proves that the modified series is stationary. Also, the order of differencing to render the data to stationary equals to ARIMA process's I(d) order that, in this case, is I (1). The results of the ADF test are demonstrated in Table 1.

Table 1 ADF results for variables

Variables	t-stat	Prob.	Δ Variables	t-stat	Prob.
LnSTP	-0.448433	0.5175	Δ LnSTP	-6.543686	0.0000
LnSCP	-0.374564	0.5465	Δ LnSCP	-6.092438	0.0000
LnORP	-0.714909	0.4041	Δ LnORP	-6.757903	0.0000
LnOIP	-0.714909	0.4041	Δ LnOIP	-6.757903	0.0000

Notes: Δ = first difference, the Significance level is 5%

The order of the autoregressive and moving average process for the ARIMA model is determined by the ACF and PACF for the LnSTP, which are represented in Fig 1.

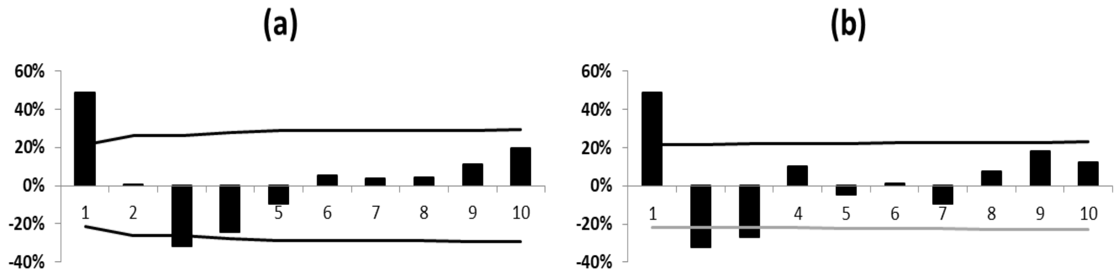

Fig.1. ACF (a) and PACF (b), source: own estimations

Due to the steep fall of ACF to zero and a significant positive spike in the first and negative spikes on second and third lags of the PACF diagram, using George Box & Jenkins (1976) guideline, initially, ARIMA (1, 1, 2) and (0,1,2) seems to be possible outcomes for the model. Therefore, further investigation is needed to generate the best model, according to BIC. After several tries to minimize BIC, it is revealed that the best model is ARIMA (0,1,2). The result of ARIMA coefficients estimation is showed in Table 2.

Table 2 ARIMA (1,1,2) Model Estimation Results for LnSTP

Estimated Coefficients::	t-Statistics	P-Values
θ_1= 0.641968	4.271296	0.0001
θ_2= 0.342790	2.762203	0.0072
Model Fit:		
R^2: 0.319300	DW: 2.022589	BIC: -3.037867
Ljung-Box Q(18) Prob.: 0.191		

Notes: DW: Durbin-Watson statistics

As seen from the results, MA coefficients are significant and also satisfies the condition of stationarity and invertibility ($-1 < \theta_1, \theta_2 < 1$, $\theta_2 - \theta_1 < 1$, $\theta_1 + \theta_2 < 1$) as described in (George Box & Jenkins, 1976).

The Ljung-Box test is used widely for testing randomness and the existence of serial correlation in the error series. It is a comprehensive statistical test for a set of autocorrelation lags instead of one to define that they are significantly different from zero, and thus they are not random. The null hypothesis for this test is that the series is not auto-correlated, and the alternate hypothesis is auto-correlated. In our model, due to the insignificant p-value, we can conclude that errors are not auto-correlated. Also, the Durbin-Watson (DW) test, which is used to detect serial correlation in the first lag, is almost 2.00, which shows no evidence of positive or negative serial correlation where it is consistent with the result of the Ljung-Box test.

For entering explanatory variables into the ARIMA system, an equation with explanatory variables of LnSCP, LnORP and, LnOIP with correspondent lags on the right side, and dependent variable LnSTP on the left side has to be formed. After then, regarding remaining patterns in residuals, the ARIMA process fitted to the residuals. All the system is optimized with consideration to BIC minimization. The results for the ARIMAX process are demonstrated in Table 3.

Table 3 ARIMAX Model Estimation Results

Estimated Coefficients:	t-Statistics	P-Values
ϕ_1= 0.454651	4.486400	0.0001
Δ LnSCP(-4) = -0.203177	-3.019891	0.0036
Δ LnOIP(-3) = -0.158213	-2.703877	0.0087
Δ LnOIP = 0.257747	3.494419	0.0008
Model Fit:		
R^2: 0.480368	DW: 1.972552	BIC: -3.150776
Ljung-Box Q(18) Prob.: 0.211		

Notes: DW: Durbin-Watson statistics

After the correct lags are selected for explanatory variables, it is found that ARIMA (1,1,0) is the best model for residuals. The condition for stationarity and invertibility for AR(1) is fulfilled $(-1 < \phi_1 < 1)$. The specified model has the lowest BIC among tested models, and regarding the DW and Ljung-Box test, there is no serial correlation in the residuals. As seen from the estimation results, the LnSCP and LnOIP only take effect after lags 4 and 3, respectively. By contrast, LnOIP has an instantaneous effect on LnSTP.

3.3 Forecast Results

In order to make an out-of-sample forecast in the multivariate ARIMAX model, initially, the forecasted values of the explanatory variables have to be defined. For this aim, the ARIMA model is used for forecasting each variable separately. Regarding the ARIMA methodology, ARIMA (1,1,1), (0,1,1) and (0,1,1) are utilized for LnSCP, LnORP and, LnOIP for forecasting July 2019 until December 2019. The results of the out-of-sample forecast for ARIMA (0,1,2) and ARIMAX (1,1,0) models are represented in Table 4.

Table 4 Forecast precision for LnSTP

	ARIMA	ARIMAX
MAPE	2.0279304%	3.034979%

Notes: MAPE: Mean Absolute Percentage Error

In this study for comparing the forecast results, Mean Absolute Percentage Error (MAPE) is used. Hyndman & Koehler (2006) stated that MAPE has clear lines and can be helpful in the case of positive and comparatively large to zero variables. The forecast results visualization of two models is shown in Fig 2.

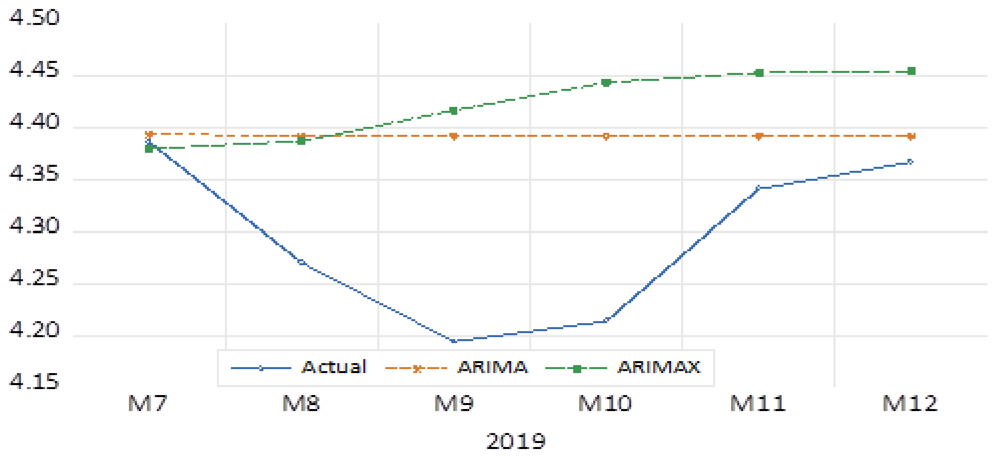

Fig. 2. Forecast Results for ARIMA and ARIMAX, source: own estimations

IV. Discussion

As observed from the results, the univariate ARIMA model outperforms the multivariate ARIMA with explanatory variables. The MAPE is lower about a half in ARIMA comparing to the ARIMAX model in the 6-month forecast horizon. While the ARIMAX model is better fitted to data in aspects of R-Square and BIC, it is not performing better than the univariate ARIMA model. The result is consistent with Peter & Silvia's (2012) findings, which compare ARIMA and ARIMAX for Gross Domestic Production (GDP) forecast. Also, the study by Kongcharoen & Kruangpradit (2013) showed mixed results for export rates between the two models, which in some cases, ARIMA yields better results than ARIMAX.

While rationally, the ARIMAX model is expected to forecast better than ARIMA due to the inclusion of the explanatory variables, it offers worse results. One explanation of this situation can be the necessity of forecasting each explanatory variable separately with univariate models to use in the ARIMAX system, which in turn adds more uncertainty to the system. Another reason might be the forecast horizon that can be effective owning to the long-run relationships between the explanatory variables.

V. Conclusion

The current study aims to forecast flat steel prices by using the ARIMAX model and compares the performance with the ARIMA model as a benchmark. In contrast with the role of explanatory variables to improve the forecast accuracy, the findings of the study prove that the ARIMA model's out-of-sample forecast results outperform the ARIMAX model. However, the model fit statistics in the ARIMAX model is better than the ARIMA model. Since the ARIMAX model uses forecasted values for explanatory variables by univariate models, the iterative nature of univariate models adds more uncertainty to the system, which may lead to worse performance. For this problem, more complex models that utilize past values of explanatory variables like Vector Autoregressive (VAR) and Vector Error Correction (VEC) can be used.

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