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Modeling the trend of construction materials industry

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Abstract

Construction materials has a key impact on the cost of construction. In construction industry it is important to foresee the trends of material prices to prevent, cost overruns during the construction stage and bankruptcy of the contractors. The material price trends have a time dependent nature, and time series analysis methods can be utilized to model and estimate them. This study focuses on modeling and forecasting the trends in material prices through Box-Jenkins methodology. In this context, an economic indicator named General Trend in Construction Materials Industry is modelled with an ARIMA (1,1,0) model. The forecasts done with the model indicate that the model can successfully predict the future values of the indicator.

Introduction

Construction materials is one of the key factors that has an impact on the cost of construction. Construction industry can be become very fragile in times of economic crisis and especially when material price fluctuations are observed. These fluctuations can be related with raw material costs, production costs, and cost of logistics. The changes in material prices can result in cost overruns which can then lead to unfinished buildings and defaulting contractors. In order to foresee the risks related to the material price fluctuations, it is important to forecast the trends in the construction material industry. The material price trends have a time dependent nature, and time series analysis methods can be utilized to estimate them. In recent years, [1] used Box-Jenkins methods to estimate the maintenance costs of construction equipment, [2] included four quarterly construction industry datasets from C&SD between 1983Q1 and 2014Q4 to accurately predict fluctuations in the construction industry by comparing the accuracy of autoregressive integrated moving average (ARIMA) and Autoregressive Neural Network (ARNET) models. [3] used Artificial Neural Networks (ANN), Linear Regression and Autoregressive Time Series (ARIMA) methods to estimate the Construction Cost Index. [4] proposed the ARIMA-ANN model to estimate construction costs and investigates whether this model can have higher accuracy than the ARIMA or ANN model. This study focuses on modeling and forecasting the trends in material prices through a well-known time series modeling methodology. The methodology is known as Box-Jenkins (ARIMA) Method and can be successfully applied to model time series of a linear nature. The following sections elaborate on the dataset, the modeling process and later presents and discusses the results of forecasts done with the model.

Material and Method

The Association of Turkish Construction Material Producers (IMSAD) is a non-profit organization in Turkey, that represents Construction Materials Industry both locally and internationally. IMSAD is well known with its Construction Material Industry Indices which are published on monthly bases. One of these indices is the Trust Index and is composed of 5 indicators. The value of each indicator is determined on monthly basis, based on responses of members to the indicator questions. The base value for the index (and all indicators) is 100 which is equal to the indicator value of August 2013 (base year/month).

In this study we have chosen to statistically model "General Trend in Construction Materials Industry" indicator which is determined as a response to the question "How has your view of the general trend in the construction materials industry in which you operate this month change compared to your view in the previous month?". The data is obtained through digitization of reports in İMSAD web site, and covers the indicator values between 08.2013-03.2021, in form of a univariate time series. In the start of the modeling process, to efficiently validate the results, the data is divided into training and test sets. The training set covered the period between 08.2013-06.2019 (71 obs.) and the test set covered the period between 07.2019-03.2021 (21.obs). We have named the training variable as 't3' as it is the third indicator of the Trust Index and named our training set as 't3train' and test dataset as 't3test' .

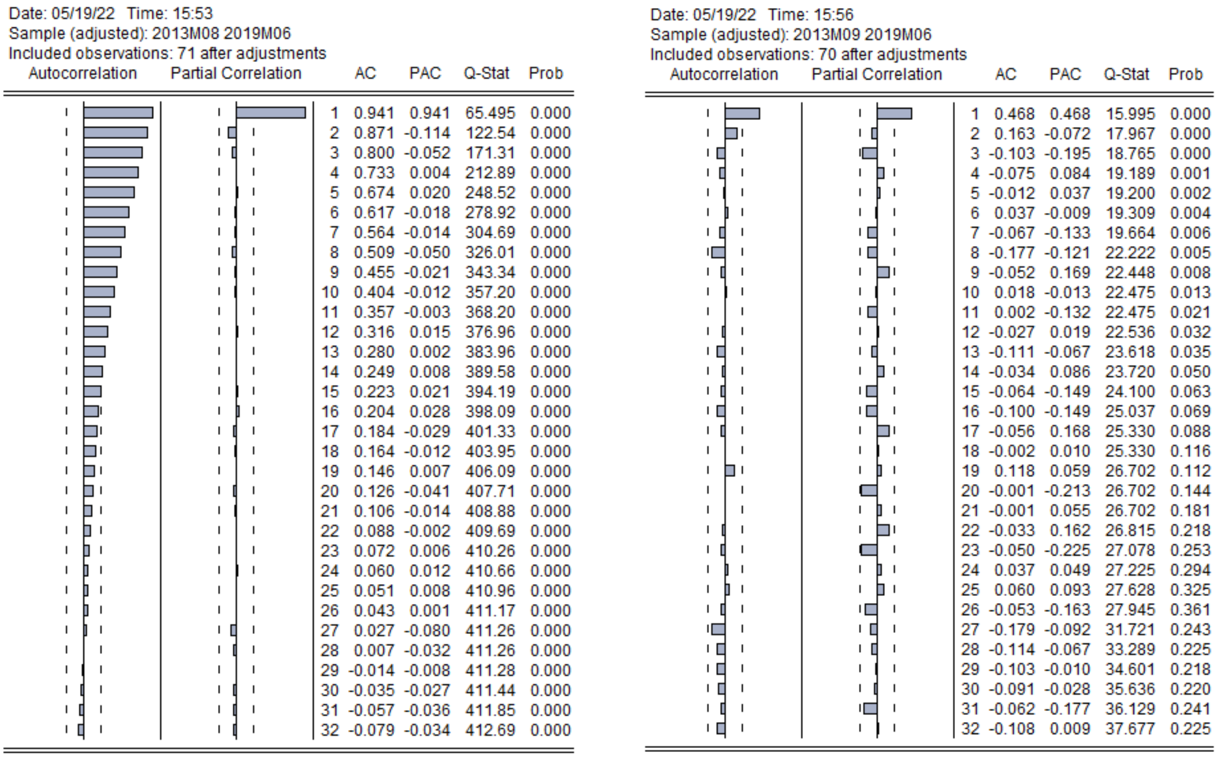

Figure 1. Correlogram of the series at Level (I=0) and at First Difference (I=1)

As illustrated in Fig 1. (left), ACF and PACF plots of the series 't3train', the series is not stationary at level (I≠0), as significant autocorrelations can be observed until Lag14. In contrast, both ACF and PACF plots of first difference of the 't3train' series tend to degrade into the confidence interval quickly i.e., at 1-2 lags. The 't3train' indicator was showing the strong signs of fitting to an ARIMA (Auto-regressive Moving Average) model. In this stage, we have generated 2 new variables by taking first difference of the series, namely dt3train and dt3test, and we further proceeded with the ARMA analysis of these new variables. The dt3train covered the period between 09.2013-06.2019 (70 obs.) and the dt3test covered the period between 08.2019-03.2021 (20.obs).

Results

The correlogram of 'dt3train' (Fig.1. right) indicate that the series have significant Autocorrelation(AC) and Partial Autocorrelation(PAC) at Lag1. According to Box-Jenkins method [5] the number of lags with significant AC and PAC values can be used to determine the nature of the model. As we found out significant AC and PAC values at Lag1 only, we considered modeling the 'dt3train' series with AR(1), MA(1) and ARMA(1,1) models. The coefficients of 3 ARMA models fitted on 'dt3train', and their significance test results are provided in Table 1,Table 2, and Table 3.

Table 1. The estimation results of the AR (1) model for dt3train

Variable	Coefficient	Standard error	t-statistic	Probability(p)
C	-0.942427	0.307625	-3.063555	0.0031
AR(1)	0.468036	0.104281	4.488203	0.0000

Table 2. The estimation results of the MA (1) model for dt3train

Variable	Coefficient	Standard error	t-statistic	Probability(p)
C	-0.855116	0.238541	-3.584769	0.0006
MA(1)	0.416428	0.108026	3.854899	0.0003

Table 3. The estimation results of the ARMA (1,1) model for dt3train

Variable	Coefficient	Standard error	t-statistic	Probability(p)
C	-0.932979	0.297270	-3.138492	0.0025
AR(1)	0.379958	0.207176	1.833991	0.0712
MA(1)	0.121375	0.229949	0.527833	0.5994

As illustrated in Table 3 The MA component of the ARMA(1,1) model was not found significant at 95% Conf. Level($p>0.05$). Thus, we have chosen to exclude ARMA(1,1) model from our evaluation. As shown in Table 1 and Table 2, coefficients of both AR(1) and MA(1) models were found significant, and according to F-test results on model significance, the overall AR(1) model was found as significant (F:20.14,$p<0.05$), and MA(1) model was also found as significant (F:16.88,$p<0.05$).

The Akaike Information Criterion (AiC) scores for AR(1) model was 3.47 and MA(1) model was 3.55. RMSE values for AR(1) and MA(1) model were found as 1.337 and 1.392. Based on both the AiC and RMSE scores, it is evident that AR(1) performs better than the MA(1) model for this dataset, and thus, the best fit model for the training data has been determined as the AR(1) model. Based on the ARMA modeling exercise, the first difference of the series (I=1) is modelled with an ARMA model, thus level of integration is 1(I=1), and the resulting ARIMA model can be expressed as ARIMA(1,1,0). The equation below (Eq.1) presents the mathematical notation of the model.

$$\begin{gathered} w_t = 0.4680 w_{t-1} - 0.9424 + \varepsilon_t \\ w_t = \Delta^1 y = y_t - y_{t-1} \end{gathered} \tag{1}$$

Discussion & Conclusion

Following the determination of the ARIMA model, two forecasts were made using the ARIMA (1,1,0) model by taking the test data 'dt3test' (20 obs.) as the ground truth. The first forecast was dynamic (out-of-sample) and the model achieved an RMSE of 1.3475, and MAE of 1.192, the second forecast was static (in-of-sample) and an RMSE of 1.073 and a MAE of 0.812 is achieved. The results have demonstrated that the "General Trend in Construction Materials Industry" indicator of the Trust Index of IMSAD can be successfully modeled and estimated with an ARIMA model.

The study aimed to model and forecast the trends in material prices through a well-known time series methodology, namely Box-Jenkins method. In parallel with its aim, "General Trend in Construction Materials Industry" indicator of IMSAD Trust Index is modelled with the proposed method. The results have demonstrated that the future values of the indicator can be estimated with high accuracy especially with in-of-sample forecasting strategy. The results have shown that Box-Jenkins methods (and ARIMA) model can be used to model trends in material prices in construction industry. Successful estimates of trends in material prices would help construction companies to take decision by better foreseeing the trends of material prices and taking precautions in advance regarding the risks related to the material price changes.

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