THE EFFECT OF INFLATION TO THE RISE OF TUITION FEE IN UNIVERSITY

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Abstrak

Dalam makalah ini, kami meninjau dampak inflasi terhadap kenaikan biaya kuliah di Universitas. Dalam sebuah perusahaan bisnis di lingkungan ekonomi, Universitas dapat menentukan harga biaya kuliah yang layak dan memprediksi harga biaya kuliah untuk menghindari kerugian. Kami membandingkan algoritma untuk memprediksi kenaikan inflasi dengan menggunakan data dari 2005-2016. Model atau teknik yang digunakan adalah metode komparatif dari ARIMA dan Time Series. Metode Time Series lebih baik digunakan dengan tingkat kesalahan RMSE 0,2414 lebih rendah dari metode CPI untuk prediksi di tahun 2017. Hasil perhitungan menunjukkan bahwa ada peningkatan pengaruh inflasi terhadap biaya kuliah di Universitas. Dengan meningkatnya biaya kuliah, biaya belajar di Universitas juga meningkat dengan menganalisis parameter yang terkait pengaruh kenaikan inflasi.

Kata kunci—Inflasi, sumbangan pembinaan pendidikan, biaya, aplikasi kampus.

Abstract

In this paper we review the effects of inflation to the rise of tuition fee in university, in an economic environment business company can determine the price of a decent tuition fee and predict the price of tuition fee to advoid losses. We compare the algoritms to predict a rise in inflation by using data from 2005-2016. Model or technique that is used is the comparative method of ARIMA and time series. Time series methods are better used with level error RMSE 0.2414 lower for prediction of CPI in 2017 years. The calculation result shows that there is an increasing influence of inflation towards the cost of tuition at the University. With the increase in tuition fees, increased to learning at the University also raised by analyzing the parameters associated with the influence of high inflation.

Keywords—Inflation, tuition fees, cost, university applications.

1. INTRODUCTION

The risk is most evident in the ever-increasing tuition our colleges and universities charge. Regardless of the reasons, higher prices mean fewer families can gain the education and training they need to grow and prosper in their communities. Traditionally-underserved students, as well as families from deeper into the middle class, find it difficult to afford a college education[1].

Economists and other analysts have long been interested in understanding the demand for higher education. Examples of such work include studies focused on quantifying price elasticities for various student populations, estimating student sensitivity to changes in financial aid packages, or constructing university-specific demand functions [2].

Each year, the number of students who apply to attend these institutions keeps getting larger, while the number of positions in their first-year students has increased only slightly. These institutions have focused primarily on maintaining or increasing their quality rather than

increasing their size (although several are now marginally doing so) and despite their increased tuition and fees, students increasingly flock to them. This has occurred in large part because, as the distribution of earnings becomes more disperse in the United States, students and their parents instinctively understand that where one goes to college may matter as much as whether one goes to college [3].

The following statement by the Canadian Association of University Teachers (2002) is typical of this point of view: "Today, however, due to record high tuition and other fees, more and more students who are interested in and capable of attending a university or college are unable to do so. Following a decade of steep increases in tuition fees and slow wage growth, modest- and middle-income households are struggling to finance the costs of higher education" (pg.1).

2. METHOD

Time series forecasting is an important area of forecasting in which past observations of the same variable are collected and analyzed to develop a model describing the underlying relationship. The model is then used to extrapolate the time series into the future. This modeling approach is particularly useful when little knowledge is available on the underlying data generating process or when there is no satisfactory explanatory model that relates the prediction variable to other explanatory variables. Much e5ort has been devoted over the past several decades to the development and improvement of time series forecasting models [4].

There are two main reasons for measuring the accuracy of predictions formulated using a time series model. First, during the development and identification stage of the model, accuracy measures are needed to compare alternative models with one another and to determine the value of the parameters that appear in the expression for the prediction function F. To identify the most accurate predictive model, each of the models considered is applied to past data, and the model with the minimum total error is selected [5].

Secondly, after a predictive model has been developed and used to generate predictions for future periods, it is necessary to periodically assess its accuracy, in order to detect any abnormality and inadequacy in the model that might arise at a later time. The evaluation of the accuracy of predictions at this stage makes it possible to determine if a model is still accurate or if a revision is required [6].

2.1 Box-Jenkins Modeling

ARIMA models employ a combination of linear operators for the representation of a time series. This type of representation has a long history, and may be traced to Yule (1921, 1927), Slutsky (1937) and Wold (1938).

The landmark contribution of Box and Jenkins (1970) was to both consolidate the models and methodologies that had existed and, more importantly, provide a cohesive framework for model building. As a result, these models are often referred to as Box-Jenkins ARIMA models, or even Box-Jenkins models [7].

The original Box-Jenkins modelling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process (e.g., Makridakis, Wheelwright and Hyndman, 1998) often add a preliminary stage of data preparation and a final stage of model application (or forecasting) [8].

2. 1.1 Data Preparation

Involves transformations and differencing. Transformations of the data (such as square roots or logarithms) can help stabilize the variance in a series where the variation changes with the level. This often happens with business and economic data. Then the data are *differenced* until there are no obvious patterns such as trend or seasonality left in the data. "Differencing" means taking the difference between consecutive observations, or between observations a year apart. The differenced data are often easier to model than the original data.

2. 1.2 Model Selection

In the Box-Jenkins framework uses various graphs based on the transformed and differenced data to try to identify potential ARIMA processes which might provide a good fit to the data. Later developments have led to other model selection tools such as Akaike's Information Criterion.

2. 1.3 Parameter Estimation

Means finding the values of the model coefficients which provide the best fit to the data. There are sophisticated computational algorithms designed to do this.

2. 14 Model Checking

involves testing the assumptions of the model to identify any areas where the model is inadequate. If the model is found to be inadequate, it is necessary to go back to Step 2 and try to identify a better model.

3. RESULT

CPI data from the years 2005-2013, as of June 2008, in June 2008 CPI is based on consumption patterns in the cost of living survey city 66 years in 2007 (2007 = 100), since January of 2014, the CPI is based on consumption patterns in the cost of living survey city 82 years in 2012 (2012 = 100) [9] [10].

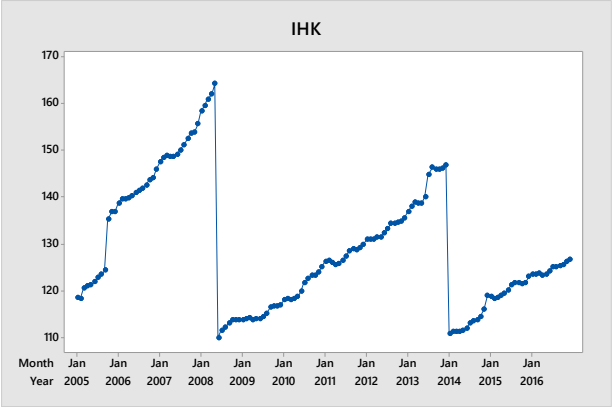

Fig.1. Data of IHK from 2005-2016

From the graph below the visible value of the autocorrelation has 6 lag and rounded value-2.00 so data are not stationary so it's not a model.

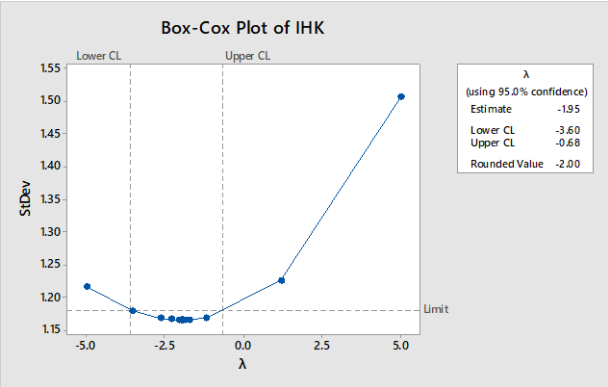

Fig.2. Graph Box-Cox Plot of IHK

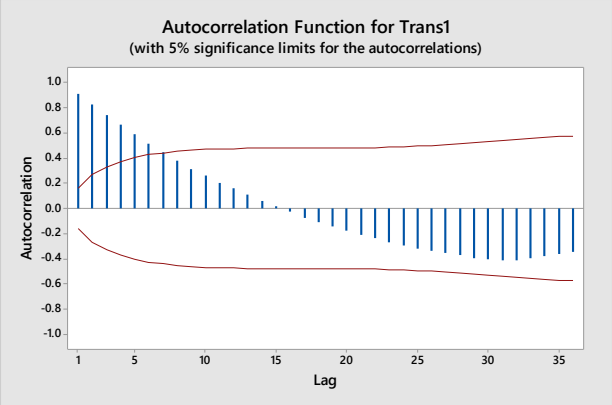

Fig.3. Graph Autocorellation Function

From the chart below indicated that the data had already been stationary because it has a rounded value 1.00 and had no lag.

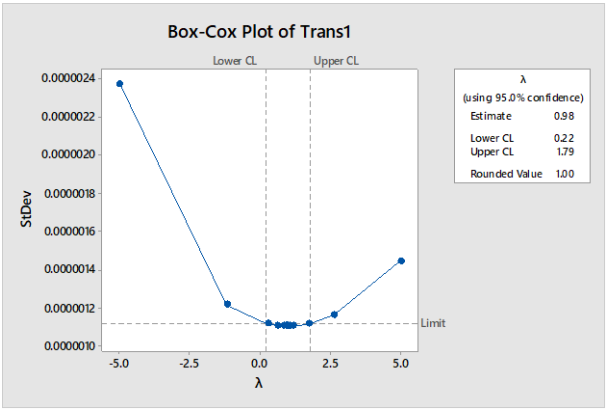

Fig.4. Graph Box-Cox Plot of Trans1

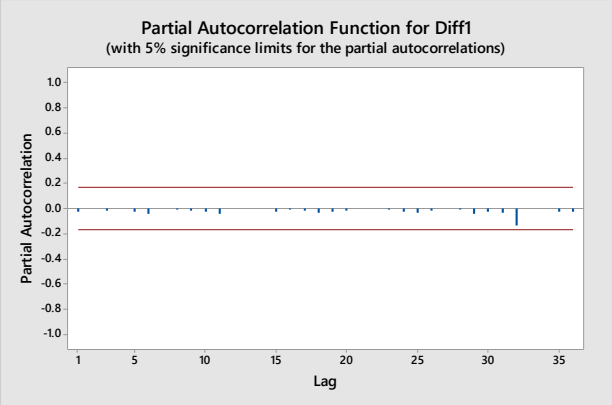

Fig.5. Graph Partial Autocorrelation

Forecasting results of visible graphs moving up and the ARIMA model in use (1,1,1).

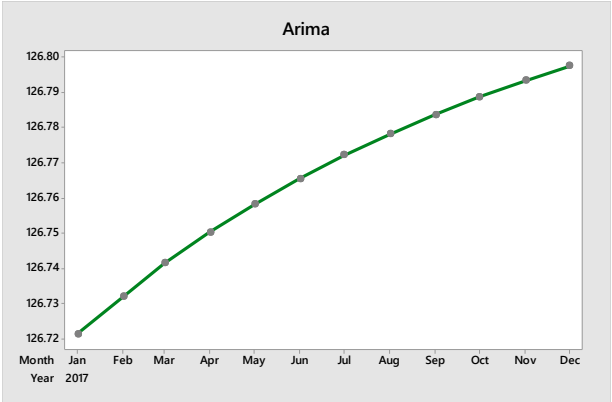

Fig.6. Graph Partial Autocorrelation

Group Method of Data Handling (GMDH) is an alternative to the traditional statistical approach. This method determines the model of the optimal complexity from the given class of models on the basis of experimental data. GMDH uses two or more subsets from a given data set for model construction, selection, and verification. It allows automatically to take into account indefiniteness concerning features of source data [11].

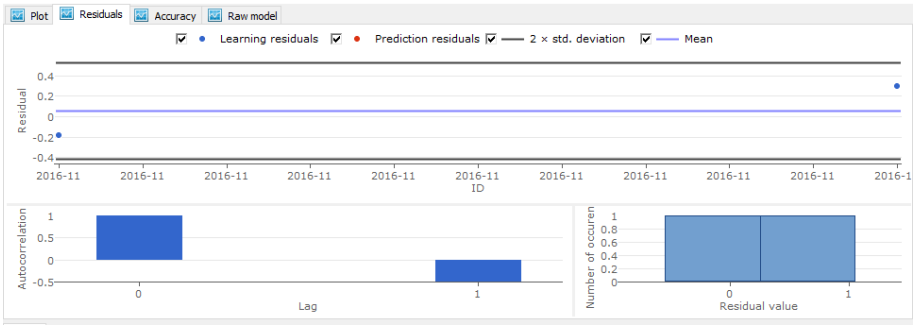

Fig.7. Residual Time Series

Prediction results using time series. prediction of actual values with the approaching almost the same increase.

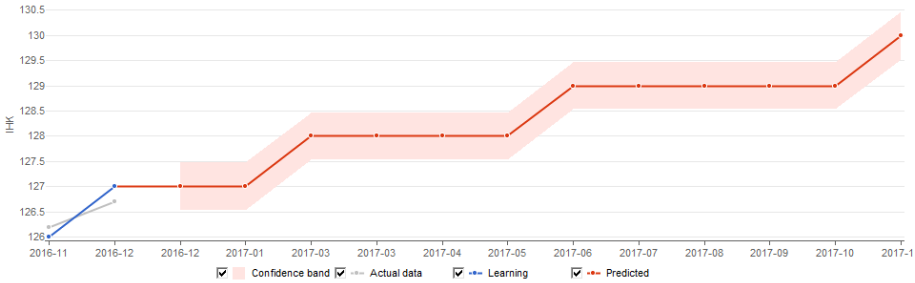

Fig.8. The result of Time Series

The results of the comparison of the two methods using the arima and time series. where the results of the prediction in discover that time series methods are better compared with the method of arima with RMSE value for time series methods 0.2414 while for larger values of RMSE arima with value 8.017107.

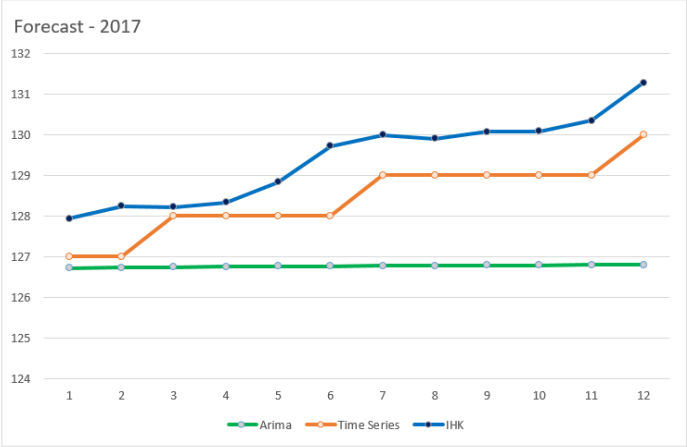

Fig.9. Comparison of the result of the prediction using ARIMA and Time Series

The results of the accuracy of the time series using GMDH software with low error values for the predicted value of the CPI in the year 2017.

Plot | Residuals | Accuracy | Raw model

Error measure: Absolute — Target: IHK of IHK

	Postprocessed learning	Postprocessed predictions
Number of observations	2	
Max. negative error	-0.18	n/a
Max. positive error	0.29	n/a
Mean absolute error (MAE)	0.235	n/a
Root mean square error (RMSE)	0.2414	n/a
Residual sum	0.11	n/a
Standard deviation of residuals	0.235	n/a
Coefficient of determination (R^2)	0.999996	n/a
Correlation	1	n/a

Fig.10. Accuracy of Time Series

4. CONCLUSION

There are several methods that can be recognized for the prediction of inflation. of the several methods we tried to combine the methods of ARIMA and Time Series to produce an accurate value. the value can have a major impact for the inflation rise in the cost of education in College, this is caused by the existence of a relationship that was designed by the rise in inflation.

In this research campus can determine the price of a decent payment for tuition each year. as well as generating value predictions with lower error value. Prediction using time series methods have RMSE value 0.2414 shows that the method of time series is better compared with the method the prediction of ARIMA.

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