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Forecasting Equity Crowdfunding Performance in Malaysia: A Comparative Analysis of Holt-Winters and ARIMA Models

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ABSTRACT

The concept of equity crowdfunding (ECF) has been seen as a potential funding platform in Malaysia especially among SMEs and startups. This alternative financing mechanism is one of the funding initiatives implemented by the government to facilitate access to capital for growing businesses. Despite its increasing significance, its future performance remains uncertain due to the dynamic nature of financial market and the changing regulatory environment. Broader macroeconomic variables such as gross domestic product (GDP), inflation rate, unemployment rate and interest rate may play an essential role in shaping the performance of the ECF. Such external factors add further uncertainty and instability within the market. Therefore, the capacity to create accurate forecasting of ECF performance is vital to predict trends in the market, risks, and assist strategic decision making for the policymakers, investors, and platform operators. In line with this need, the study aims to forecast the performance of ECF based on statistical time-series models which can be beneficial to the stakeholders. The monthly data from 2017 to 2022 were collected from the Department of Statistics Malaysia (DOSM) and Securities Commission Malaysia (SC), analysed using Holt-Winters Exponential Smoothing model and the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) method. The measure of model performance was based on Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results indicated that although Holt-Winters fit the short-term changes, ARIMA was better suited to overview changes in the systems and long-run trends, illustrating the dynamics of the crowdfunding ecosystem. These finding demonstrate the evolving role of ECF as both a financing channel and an indicator of economy changes. Therefore, this research can contribute to the theoretical knowledge while leading to a valuable application of the current findings by practitioners in policymaking, investors, and the operation of ECF platforms.

Keywords:

Equity Crowdfunding (ECF); Autoregressive Integrated Moving Average (ARIMA); Holt-Winters Additive Model; exponential smoothing

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1. Introduction

ECF has emerged as a crucial mechanism for economic empowerment, which democratizes access to capital, enabling individuals and small businesses to break through financial barriers that previously limit their growth. It is not only funds projects that might have struggled to secure financing through traditional channels but also fosters a culture of innovation [1-3]. Under government initiatives to promote entrepreneurship in the country, ECF has shown rapid growth, but with fluctuating performance due to other market factors such as market regulations, macroeconomic influences like GDP, inflation, unemployment, and interest rate. Nevertheless, the economic importance of ECF notwithstanding, there is limited empirical studies in Malaysia related to ECF forecasting to make informed decisions by policymakers, investors, and platform operators. Addressing this gap, this paper compares the performance of the Holt-Winters Exponential Smoothing and ARIMA models to determine the most accurate approach to be use in predicting the trends in ECF gaining insight of both short-term changes and long-term dynamic in the Malaysian crowdfunding ecosystem.

2. Literature Review

Generally, in literature, forecasting may be conducted using various approaches, such as the statistical approach, artificial intelligence approach, and others. Fundamentally the dynamics on forecasting the ECF performance with the economic factors follows an underpinning theory of Adaptive Expectations Theory (AET). According to this theory, the anticipations of the future event are framed by the previous trends and are modified with passing time, which is characteristic of the forecasting models such as Holt-Winters and ARIMA. Through the application of AET, the research justifies the position of using the historical data as a foundation upon which it relays the future performance of the Malaysian ECF market. Nevertheless, the dilemma in forecasting approach determination becomes the researcher's predicament, because every forecasting approach has its own drawbacks. Following the objective of the study to present both diagnostic and predictive information on the performance of ECF, forecasting models are included. Although recent trends in financial forecasting had led to the incorporation of Artificial Intelligence (AI) models, such as neural networks and machine learning algorithms, their capability in forecasting ECF usage remain limited. In this literature review, the ongoing debate surrounds forecasting methodologies, considering artificial intelligence (AI), exponential smoothing, and Box-Jenkins techniques. By evaluating the strengths and weaknesses of these approaches, the study aims to shed light on the most effective forecasting methods for crowdfunding and their relevance in the context of macroeconomic indicators. A comprehensive literature review highlights certain drawbacks for artificial intelligence (AI) to display sensitive responsiveness to historical data fluctuations; a phenomenon identified in studies by Pozen *et al*., [4] and Kurani *et al*., [5]. The significance of data quality in time series analysis is underscored as incomplete, inaccurate, outdated, or biased data can substantially compromise the dependability of forecasting, as emphasized by Ashta *et al*., [6].

Therefore, considering the practical constraints of AI being applied to smaller platforms, it is more viable to predict ECF performance using traditional forecasting measures such as the use of Exponential Smoothing. This forecasting methods are vital in predicting a future ECF outcome across different macroeconomic conditions. Exponential smoothing, a traditional time series forecasting method, has long been a staple in forecasting literature. Its simplicity and effectiveness have found applications in various domains, including finance and economics. Hyndman *et al*., [7] emphasize some of the most successful forecasting methods are based on the concept of exponential smoothing

It requires minimal computational resources, making it accessible to a wide range of users. Furthermore, Gardner and Everette [8] highlighted the significant methodological advancement through the development of a robust method for smoothing damped multiplicative, and have demonstrated the usefulness of exponential smoothing in capturing trends and seasonality. In addition, Ostertagová *et al*., [9] pointed out that the performance characteristics of the model should be verified or validated by comparing its forecast with historical data for the process it was designed to forecast. According to Kuzhda [10], exponential smoothing with its advanced version of Holt-Winters Additive models efficiently track short-term patterns in financial time series, especially where data exhibit regular patterns.

Nevertheless, while Exponential Smoothing may practically give useful benefit in the short-term recognition, it might be limited in its ability to recognize nonlinear or longer forecasting horizon. To address these challenges, The Box-Jenkins approach, based on autoregressive integrated moving average (ARIMA) models, is another well-established forecasting technique [11]. Its capacity to capture complex temporal dependencies has led to its application in predicting ECF outcomes. Researchers like Hassan [12] have explored its potential in this context where the study used the Box-Jenkins method and ARIMA models to analyze and forecast Somalia's GDP. In the meantime, Dixon [13] proved that, ARIMA can be used as a robust forecasting tool that can deliver multi-step prediction capabilities to financial time-series data, hence, making it practical to use it particularly in a volatile market regime. Nyoni [14] also indicated the advantage of ARIMA models relative to the use of autocorrelation in economic time series as well as seasonal patterns that make them sufficient to analyze ECF platforms that are influenced by several economic indicators. Nevertheless, Box-Jenkins method may require extensive preprocessing and model selection and can sometimes give inaccurate forecasts, particularly on nonlinear ECF data [15].

3. Forecasting Method

3.1 The Exponential Smoothing Approach

Exponential smoothing technique is widely used in business as well as econometrics field of study for the purpose of forecasting. There include Simple Exponential Smoothing (SES), Double Exponential Smoothing (Holt Method) and Triple Exponential Smoothing (Holt-Winters Method). Often referred to as the triple exponential smoothing model, the Holt-Winters model is a time series forecasting technique which incorporates three elements; the level, trend, and seasonality. The approach can capture and predicting time series involving a trend and seasonal components. This qualifies it to be used when the data show systematic patterns over time [16,17]. This model is however, normally suitable in short time forecasts. In the meantime, the Simple Exponential Smoothing (SES) model can be described as a single smoothing parameter and is suitable for situations where a quick and simple model is sufficient. In addition, SES has the benefit of being able to adapt easily to changes in data, particularly in a situation where the time series data subject to frequent changes, or exhibits short-term fluctuations. Therefore, Simple Exponential Smoothing (SES) stands out as the desirable model to be utilized in the research based on such argument, with regards to ECF campaign data. It is common to find short-term variations in the amount of funding of the data of the ECF campaigns, which the SES can respond quickly to these changes, and can serve insights into immediate trends. SES effectively reduces noise which gives a clearer picture of the funding pattern, easier facilitation of patterns.

SES $(F\_t\ ) = \alpha \times X\_(t-1)$+ (1- a) $\times F\_(t-1)$ (1)

Description:

a = smoothing constant

SES = the forecasting value on period t

$F\_(t-1)$ = the SES value on period t-1

3.2 Autoregressive Integrated Moving Average (ARIMA)

It is a systematic forecasting, control, and analysis of time series. It involves several sequential steps which include model identification, estimation of its parameters, verification of diagnostics and forecasting [12]. The overall usefulness of this methodology as a means of time series forecasting and modelling has made it widely applied in a variety of fields including but not limited to finance, engineering, and econometrics. The utilization of autoregressive integrated moving average (ARIMA) models, which are estimated iteratively via Box-Jenkins method [14]. The trait makes the approach a valuable tool in measuring the complexities of time series data.

4. Forecasting Technique Results
4.1 Exponential Smoothing

Tables 1 below indicates the outcomes of the forecasting technique on the ECF performance in accordance with the amount of equity crowdfunding. Four Smoothing techniques were employed to examine the data including, Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), Holt Winters (No Seasonal) and Holt-Winters (Additive). The analysis presented below gives some insights about the comparative performance of these approaches based on the provided metrics: Alpha, Beta, Gamma levels, SSR, RMSE, EOP levels and Seasonality.

Table 1
Results for forecasting methods for ECF amount

Metric	SES	DES	Holt-Winters (No Seasonal)	Holt-Winters Additive
Alpha	0.0500	0.05	0.1899	0.05
Beta	-	-	0.3200	1
Gamma	-	-	-	0
SSR	0.3851	0.2584	0.2336	0.1970
RMSE	0.0731	0.0599	0.0570	0.0523
End of Period Levels	2.7676	2.8108	2.7582	2.7610
Seasonality	-	-	-	Monthly Seasonal Factors Included

According to the SES model, the smoothing parameter alpha (alpha) stands at 0.0500 and this implies that the model does not place a lot of emphasis on present observations but instead relies a lot on historical trends. This low α is appropriate for cases where data variance is not expected to be abrupt or when the data requires more constant equilibrium. The model's performance is evaluated using two key error measures. The sum of squared residual (SSR), which is 0.3851, is a small value which shows the model fits well to the data. This is proved by the Root Mean Square Error (RMSE) value of 0.0731, which further confirms the accuracy of the forecast, indicating minimal deviation between observed and predicted values. The end of period (EOP) level is 2.7676 that would represent the predetermined level of ECF amount at the end of the observation period. This value represents the overall trend and acts as the foundation for future predictions. Next, the Double Exponential Smoothing (DES), the addition of trend smoothing, also yields a good result reflected by a reduced SSR of 0.2584 and RMSE of 0.0599. The EOP level at 2.8108 highlights the model's sensitivity to upward trends, making DES a better choice for data with directional movements.

The Holt-Winters (No Seasonal) model further increases trend adaptation by adding a β parameter with a value of 0.3200 and an α of 0.1899. This leads to an SSR of 0.2336 and RMSE of 0.0570, which are improvements over the original DES used in this study. The EOP level of 2.7582 also proves it works well with trend-dominated data but lack consideration of seasonality. Finally, the Holt-Winters (Additive Seasonal) model gives the detailed analysis with both trend and seasonal adjustments. The current method provides the lowest SSR of 0.1970 and RMSE of 0.0523 to accurately estimate ECF dynamics. The fluctuation in monthly seasonality incorporated in this model makes it the best performing model. This has been adjusted at an end-of-period level of 2.7610.

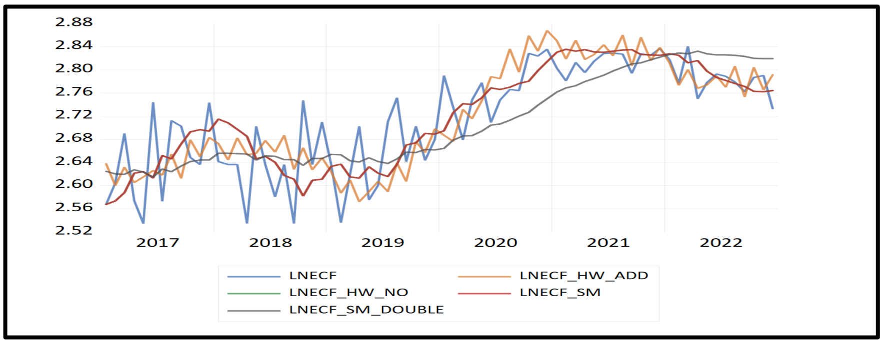

Fig. 1. Forecasting comparison for ECF amount [9]

Figure 1 represents the ECF chart, which takes the actual amount of ECF and facilitates the comparison of the observed data with the results of each forecasting method. Holt Winters Additive Seasonal (HW_ADD), Holt Winters No Seasonal (HW_NO), Single Exponential Smoothing (SES), and Double Exponential Smoothing (DES) models have been included in the graph, comparing them with the actual values in the form of blue line. Among these, HW_ADD model (orange line) closely aligns with the observed data and can show seasonal variation and trends as supported by superior error statistic. The HW_NO model (green line) fits the overall data but lacks seasonal sensitivity. However, the HWAS and HWNS models appear as a single overlapping line in the graph. This is due to the fact that in the estimates of the HWAS model, gamma parameter has been put to zero which in essence effectively disables the seasonal component. Therefore, the HWAS model performs in a similar way to the HWNS model because it excludes seasonality while comprising both level and trend. When comparing the two models, SES and DES give base line smoothing techniques, but DES possesses greater resolution particularly for data sets with trends. However, the drawback of the models is that a component for seasonality cannot be estimated from the data if there are strong periodic fluctuations in the data. This gives HWNS a level and trend advantage, especially for the trend-dominated dataset. At the same time, the HWAS model, in pursuit of level, trend, and seasonality, if it was initially configured with a non-zero gamma parameter, could prove to be more efficient than other models.

3.2 Results of Box Jenkins (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) has been developed based on the autocorrelation function (ACF) and partial autocorrelation function (PACF), derived from 32 lag from the collected data on ECF metric of ECF amount. The first and most important stage in Box Jenkins approach is the identification of an appropriate model to know whether the data is stationary or non-stationary.

3.2.1 ARIMA Models and Ljung-Box Test analysis for ECF amount

The results in Table 2 reveal the forecasting performance of different ARIMA models for the ECF amount metric based on the error measures (RMSE, MAE, and MAPE) and the Ljung-Box Q-Statistic together with its probability value (p-value). These metrics evaluate predictive accuracy and adequacy of the models based on the analysis of the residuals.

Table 2
Performance metric of ARIMA Models for ECF amount with Ljung-Box Test results

ECF Metric	Model	RMSE	MAE	MAPE	Q-Stat	Prob
ECF Amount	ARIMA (1,1,1)	0.0504	0.0378	1.4066	1.4681	0.226
	ARIMA (1,1,2)	0.0504	0.0377	1.4049	1.3846	0.239
	ARIMA (2,1,1)	0.0506	0.0379	1.4111	1.3909	0.238
	ARIMA (2,1,2)	0.0507	0.0381	1.4180	2.3222	0.128

The ARIMA (1,1,2) model emerges as the best result since it has the lowest value of RMSE (0.0504), MAE (0.0377), and MAPE (1.4049). These values show that the model selected can generate forecasts with minimal deviations from the actual data. Furthermore, the Ljung-Box Q-Statistic value of this model is 1.3846 with p-value of 0.239, therefore suggesting no significant autocorrelation in the residuals. This indicates that the proposed model meets the assumptions required for accurate forecasting. The next best model is the ARIMA (1,1,1) model with an RMSE equal to 0.0504, while MAE stood at 0.0378, and MAPE at 1.4066. Nevertheless, its error measures are slightly higher than that of ARIMA (1,1,2). In its residuals test, its value of Q-statistic (1.4681) and the p-value (0.226) indicate that the models' residuals are independent. However, the models ARIMA (2,1,1) and ARIMA (2,1,2) presented comparatively a weaker performance. The first result set shows that ARIMA (2,1,1) generated slightly higher RMSE (0.0506), MAE (0.0379), and MAPE (1.4111). The last result shows that ARIMA (2,1,2) brought the poorest performance with RMSE (0.0507), MAE (0.0381), and MAPE (1.4180). Furthermore, the lower Q-statistic of ARIMA (2,1,2) (2.3222) with a lower p-value of 0.128 also suggest that while it has no problem detecting residual autocorrelation, the model is less robust in capturing the underlying data patterns compared to ARIMA(1,1,2).

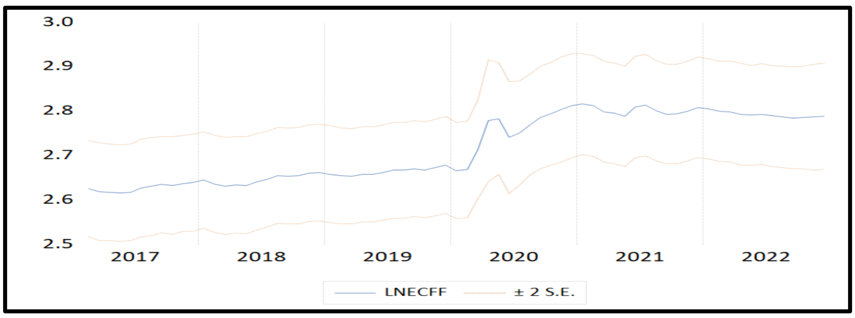

Fig. 2 Forecasted versus actual values of ECF amount with confidence intervals [9]

Figure 2 illustrates the graphical depiction of actual and forecasted values of ECF amount for years 2017 to 2022 with +-2 standard errors of confidence interval. The chart depicts the trend captured by ARIMA (1,1,2), demonstrating its effectiveness in tracking the variations and patterns in the actual data. The forecasted line closely follows the actual data points, especially in phases in which there are stable trends, hence showing the movement of the model in reflecting real events. Such discrepancies are relatively minimal because of the model's robustness in predicting short-term changes and long-term trends. The forecast intervals contain most of the actual data points, hence confirming the model's capability of giving reliable forecasts within stipulated error bounds. Furthermore, the forecast line shows smooth transitions, implying that the ARIMA (1,1,2) captures the trend and the noise present in the data well without overfitting. This would ensure that the model not only reflects on the previous behaviour of the ECF amount, but also comes up with reliable future predictions. Therefore, based on the quantitative characteristics and the correspondence visually presented in Figure 5.4, ARIMA(1,1,2) model can be deemed the most appropriate for predicting ECF amount. It represents a uniquely effective means for tracking historical ARIMA and forecasting future ECF performance trends.

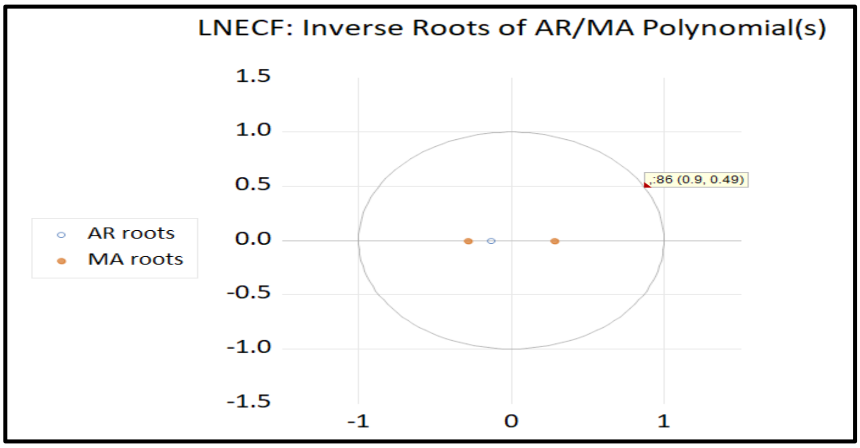

Fig. 3. Inverse roots of AR and MA polynomials for ECF stability analysis [9]

Figure 3 depicts the inverse roots of autoregressive (AR) and moving average (MA) polynomials arising from the ARIMA model chosen for forecasting the logarithm of ECF performance (ECF). This diagnostic tool is relevant for the ARIMA model to check that the parameters obtained provide a stationary and invertible process. The stability is ensured if all roots of related polynomial are inside of unit circle, which also means that the model is stationary and invertible. In this case, the roots of AR, corresponding to the hollow blue circle, and the roots of MA, depicted by the solid orange circle, are both located well within the unit circle. This confirms that the ARIMA model fulfils the essentials for reliable forecasting. Notably, one of the MA roots is positioned near the unit circle with the value of 0.9, which indicates the capability of the model to identify stable features of the data. This suggests that the MA coefficient shrinks as more lags are included, also implicating that this component captures the right profile of decay of the autocorrelations, which is an essential component of time series forecasting. However, the proximity of this root is located very close to the boundary and warrants attention in future application, since it may be sensitive to changes in patterns of data.

Overall, the graph supports the robustness of the ARIMA model in forecasting ECF amount. The placement of the roots enhances the stability of the model and shows that the model meets theoretical assumptions to adequately describe the performance of ECF amount over time. This analysis supports the model's reliability in interpreting and forecasting trends within the ECF ecosystem.

4. Conclusion

A comparison of the mentioned approaches demonstrated that different methods have unique advantages and disadvantages. The Holt-Winters Additive model of Exponential Smoothing was particularly effective in detecting short-term movements and clear fluctuations, providing a simpler method that is ideal for the series that have well-defined and stable patterns of seasonality. Nonetheless, ARIMA has benefits in revealing long-term bindings and autocorrelations, and therefore is more suitable for forecasting in the complicated and fluctuant ECF market in Malaysia. Relative to financial systems in testing and development, Susruth [18] stated that ARIMA remains essential given its versatility and precision in emerging uncertainty.

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