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Araştırma Makalesi ● Research Article

Predicting the Profitability of the Stock Market during a Pandemic

Pandemi Döneminde Borsa Karlılığının Tahmini

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MAKALE BİLGİSİ

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ÖZET

Bu makale, pandeminin başlangıcında en çok etkilenen on ülkenin borsalarının karlılığını tahmin etmede Covid-19 pandemisinin etkisini araştırmaktadır. Çalışma, analiz için Yapay Sinir Ağı modellerini kullandı. Spesifik olarak, Geriye Yayılım (BP) ve İleri Beslemeli (FF) Sinir Ağı modelleri, borsanın günlük bir zaman diliminde karlılığını tahmin etmek için kullanılır. Covid-19 dikkate alındığında, tahmin sonucu, oluşturulan Sinir Ağının Brezilya ve Çin'deki borsanın karlılığını tahmin etme yeteneğinde esnek olduğunu gösteriyor. Ancak Almanya, Rusya, Türkiye ve Amerika Birleşik Devletleri örneğinde, Sinir Ağı tahmin yeteneğinde kısmen esnektir; Bazı dönemlerde tahmin edilen kârlılık fiili kârlılıktan sapmıştır. Örneklemde kalan ülkeler için Yapay Sinir Ağının zayıf bir tahmin gücüne sahip olduğu bulunmuştur.

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ABSTRACT

This paper investigates the impact of the Covid-19 pandemic in predicting the profitability of the stock market of the ten most hit countries at the beginning of the pandemic. The study employed the Artificial Neural Network models for the analysis. Specifically, the Backward Propagation (BP) and Feed-Forward (FF) Neural Network models are used to predict the profitability of the stock market on a daily time frame. Taking Covid-19 into account, the estimation result shows that the Neural Network built is resilient in its ability to forecast the profitability of the stock market in Brazil and China. However, in the case of Germany, Russia, Turkey, and the United States, the Neural Network is partly resilient in its forecasting ability; predicted profitability deviated from the actual profitability in some of the periods. For the remaining countries in the sample, the Artificial Neural Network is found to have a weak prediction power.

Foundeed in China's Wuhan province in December 2019, the novel coronavirus has spread to more than 200 countries and territories throughout the world since then. A Public Health Emergency of International Concern was declared in January 2020, and the World Health Organization (WHO) designated Corona Virus Disease (Covid-19) in February 2020 as the cause of the outbreak. The spread of the virus has resulted in a variety of dangers, including physical, economic, financial, psychological, and other problems, among others. The book Covid-19 was published in China in late January 2020, and it has since been translated into three other languages (Thailand, Japan, and the Republic of Korea). Those countries responded by putting in place protocols to assist health officials in the detection of cases. These processes included things like airport monitoring, contact tracing, quarantine, and other measures. Since then, the virus has spread to other regions of the world, increasing the total number of laboratory-confirmed cases in about 200 countries to 5,106,100, with 330,004 deaths, to 5,106,100 cases in approximately 200 countries (as of 21 May 2020).

Because there is currently no vaccination or treatment for the Covid-19 infection, the most effective way is to prevent the illness from becoming widespread. Containment/prevention methods implemented by countries include restrictions on foreign and internal movement, commercial closures, and, in extreme cases, the complete lockdown of the country. These life-saving measures are not without their downsides, one of which is the financial toll they will have on society. Global economic growth was negatively impacted by the emergence of this disease and the government's response to this outbreak. This pandemic has also posed enormous challenges to the global financial markets, exposing investors to an unprecedented risk of market loss as a result of the outbreak (see, Goodell, 2020). It's important to note that certain factors have had a significant impact on the development of the health crisis into an economic and financial catastrophe in recent years (Ramelli & Wagner, 2020). During the immediate aftermath of an outbreak, public sentiment is bolstered by social media and technological developments in information flow speed, which serve as possible channels for spreading misinformation and boosting market pessimism (Corbet, Larkin, & Lucey, 2020). Aside from that, the ever-growing fear of death and infection suffocates trade and causes wild swings in the price of goods and services (Ding, Levine, Lin, & Xie, 2020). Reports on Covid-19 tend to be appealing in terms of their ability to move financial markets (see, Baker et al., 2020; Sharif, Aloui, & Yarovaya, 2020). As a result, central banks employed their "whatever it takes" policy to keep the financial markets afloat and prevent them from collapsing under the weight of the imminent danger that threatened to destroy them.

The estimated geographical scope of the virus's propagation and prevalence of infections, as well as the potential for a contagion effect on economies around the world, could not be predicted reliably during the outbreak's initial phase of development. Consequently, it became more difficult to allocate resources in order to effectively contain the outbreak. It wasn't until after the disease's spread and destruction had caused such widespread devastation that measures to prevent the disease's spread were put in place, including quarantine, self-isolation, social distancing, border closure, travel restrictions, and the prohibition of large gatherings. Considering, the stringent measures taken by several countries to flatten or crush the Covid-19 curve, it became clear that they had a significant impact on the economy through the restriction of economic activities, with industries such as aviation and tourism bearing the brunt of the consequences (see, Zhang, Hu, & Ji, 2020). Thus, determining the impact of systematic risk on the global stock market becomes critical. Indeed, according to the Efficient Market Hypothesis (EMH), stock price behaviour can be predicted using specific market information sources. As a result, the importance of studying and forecasting Covid-19's economic impact cannot be emphasized. In light of this, this research employs a mathematical model based on a neural network to examine how financial markets in major affected economies throughout the world behaved to Covid-19 and to forecast its profitability in the event of a pandemic. In the scientific literature, the application of neural networks for various epidemics and financial market risks has been thoroughly documented (see, e.g., Lopez, Manogaran, & Jagan Mohan, 2017; Laureano-Rosario et al., 2018. etc.).

Because of its explanatory power and flexibility to represent nonlinearities and big data, the neural network outperforms classic forecasting approaches such as autoregressive models. Furthermore, when the inputs are highly correlated, the neural network estimates perform better. However, the research shows that this methodology is underutilized, leaving room for additional implementation. This model can also be used dynamically during an outbreak to quickly determine the spread of systematic risk. The application of machine learning techniques for stock price forecasting is also gaining popularity.

1. MATERIAL AND METHOD

In this study, the EMH was employed as a hypothetical framework to analyse the findings. A study of the EMH indicated that the behaviour of an efficient market can be predicted linearly, implying that the behaviour of stock prices can be predicted based on particular market information sources. Although the linear models are still reliable in an inefficient state, the dependability of the models is put into question due to the presence of additional sources of information, such as shocks that might produce nonlinearities and cycles. The Covid-19 epidemic forced the closure of most economies, developed and developing, in order to reduce the likelihood of the virus spreading. The Neural Network models were used to assess the stock market's predictability, as well as whether the EMH holds for the most affected economies during the Covid-19 pandemic. The brief period was chosen because it was during the early stages of the Covid-19 epidemic when there were many doubts about the pandemic's conclusion. A lot of noise (news) and information asymmetry has resulted in the study's necessity to test for stock market returns' predictability with the predictive models.

The Multi-Layer Perceptron MLP Backward Propagation and Feed Forward Neural Network models are used to investigate and forecast the stock market's response to Covid-19 dynamics on a daily temporal scale and at a country level for a forecast window of 10-15 days to the previously recorded case. Because Covid-19's spreads on the global economy are nonlinear, it is considered a complex phenomenon. When the inputs are highly correlated or the systems are nonlinear, the Artificial Neural

Network estimates perform better. With the hidden layer included in the multi-layer Neural Network model, an approximation generalization can be made (see, Chatterjee, Ayadi, & Boone, 2000; Marius-Constantin, Balas, Perescu-Popescu, & Mastorakis, 2009). The feed-forward and backward propagation phases of the algorithm are nested around input, output, and hidden layers describing the relationship.

The feed-forward model, on the other hand, is dependent on both current and previous inputs or independent variables (new cases, death, active cases, and stock return lag), whereas the backward propagation model is solely dependent on past outputs or dependent variables (stock index) in the network. The activation/disposal unit implements the relation below by transferring each component of the input vector (i.e. new cases, death, active cases, and stock return lag) to the hidden layer (the layer in which information travels from inputs to outputs in one direction). The nodes in the hidden layer can be used to model. They're concealed because their genuine values can't be seen directly from the system's inputs and outputs.

Under the neural network model, the chosen inputs (independent variables) are integrated until a threshold is reached. Once a threshold is reached, an action is transmitted with a delay to other units it is connected to.

$$Z_k = \sum_{j=1}^{n} \lambda^k \psi(x_j + k\varepsilon) + k \ldots\ldots Eqn. 1, \qquad k = 1,2,\ldots\ldots,h$$

In line with Feng (2003), the hidden layer is assumed to be specified using a nonlinear activation that takes the form of a sigmoid function below.

$$Z_k = \frac{1}{1 + exp\left[-(\sum_{j=1}^{n} W_{kj}X_j + \theta_k)\right]} \ldots\ldots Eqn. 2$$

Where Z_k is the real output of unit *k* in the hidden layer; λ^k is the learning parameter in-unit *k* i.e. the parameter that controls the rate at which the weight changes; n is the number of nodes in the input layer; $\psi(*)$ is the monotonically increasing function independent of *f(*)*; x_j is the input unit *j*; $k\varepsilon$ is a node to a change in weight; the synaptic weight, the strength or amplitude of the connection between hidden unit k and the input unit j is W_{kj}; and the disposal value of unit k is θ_k. The estimated output unit i of the network is obtained from the function below:

$$\hat{y}_i = \sum_{k=1}^{h} g_i(Z_k) \ldots\ldots Eqn. 3$$

$$i = 1,2,\ldots.,m$$

$$g_i(Z_k) = W_{ik}Z_k \ldots. Eqn. 4$$

Where $g_i(*)$ is the real constant function; h is the number of nodes (units/) in the hidden layer. Determining the process of the MLP requires the error function to be specified and described appropriately as:

$$\varepsilon(w) = \sum_{k=1}^{k} e(w) \ldots\ldots Eqn. 5$$

With the overall error stated thus:

$$e(w) = \frac{1}{2}\sum_{k=1}^{k} \|y_k - \hat{y}_k\|^2 \ldots\ldots Eqn. 6$$

The actual and estimated output y_k and $\hat{y}_k$ in unit k respectively are compared to arrive at the squared error for each unit in the system. The error function defines how far the actual output is from the estimated output. In this manner, the network error is propagated backward in a recursive way over the entire network to arrive at the minimum error by adjusting the weights (see Feng, Li, Cen, & Huang, 2003; Yu, Qin, Chen, & Parmar, 2020)

For the output layer

$$\frac{\partial e(\omega)}{\partial \omega_{ik}(t)} = \eta \sum_{k=1}^{s} [(y_i - \hat{y}_i)z_k] \ldots\ldots Eqn. 7$$

$$i = 1,2,\ldots,m;$$

$$k = 1,2,\ldots,h$$

The derivative of the error function to minimise the error gives the direction to be moved within the weight. Where y_i is the target output, $\hat{y}_i$ is the actual output of unit i, and z_k is as defined previously.

$$\frac{\partial e(\omega)}{\partial \omega_{ik}(t)} = \eta \sum_{r=1}^{s} \left\{ \sum_{i=1}^{m} [(y_i - \hat{y}_i)\omega_{ik}(t)]\, z_k(1 - z_k)x_j \right\} \ldots\ldots\ Eqn. 8$$

$$j = 1,2,\ldots,n+1$$

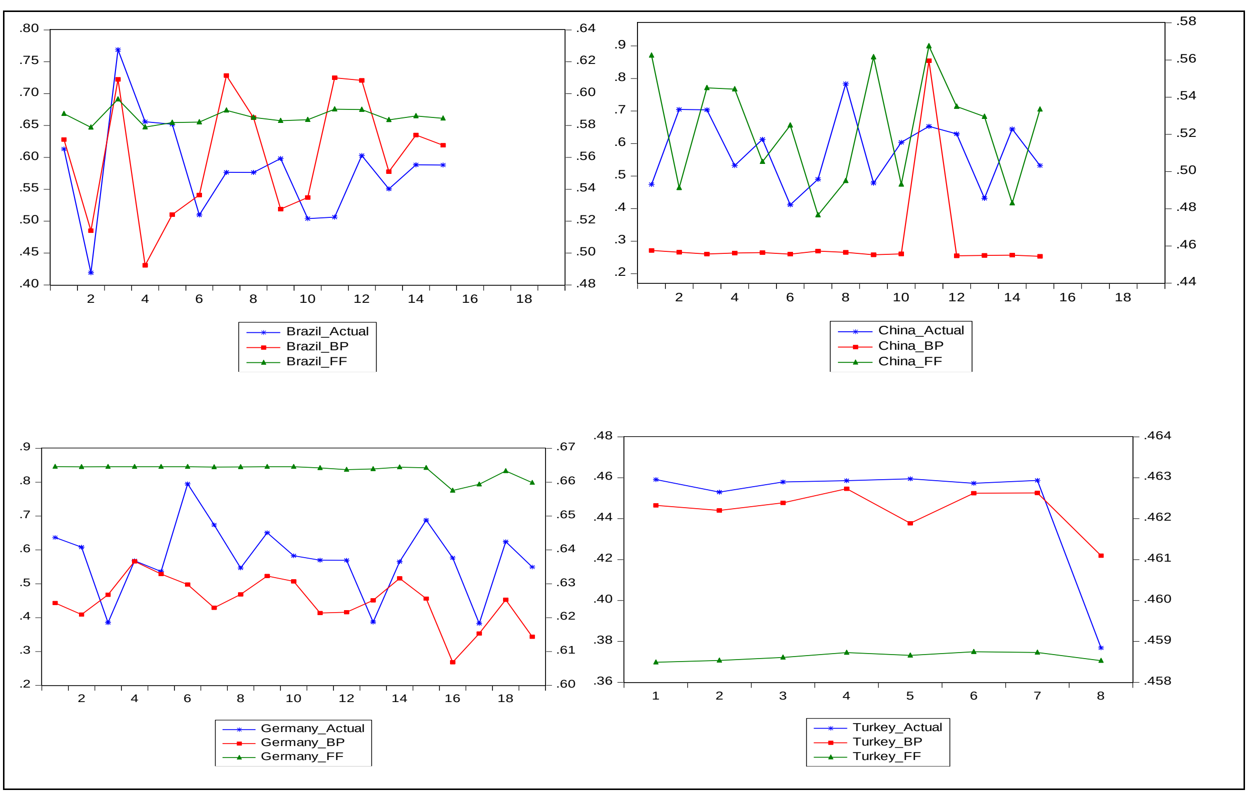
$$\omega_{k(n+1)}(t) = \theta_k(t), x_{n+1} = 1 \ldots\ldots\ Eqn. 9$$

Whereas is training sample assemble and m is the number of neurons in the output layer of the network. Feed-forward is part of the backward propagation algorithm. The values are feed-forwarded before calculating the errors and propagate back to the layers.

The Covid-19 data for countries on the top ten list of confirmed cases were collected from the University of Oxford Our World In Data database (according to data on May 1, 2020) except Iran due to stock market data unavailability. Daily stock indices were collected from investing.com database. The indices are as follows; US S&P 500, Russia MOEX, Brazil BOVESPA, UK FTSE 100, Germany DAX, Italy, FTSEMIB, Turkey BIST100, Spain IBEX35, China SSEC, and France CAC40. In this study, the stock indices were transformed in line with Lim & Liew (2003) to a continuously compounded percentage returns.

2. RESULTS AND DISCUSSION

This section shows the results of the stock market's projected profitability when the impact of Covid19 is taken into account. When it comes to training the network, 75 percent of the data is used, and the remaining 25 percent is used for prediction. To make it easier to compare the two network models, a graph showing the expected values for each model against the actual values is presented. For the 10 countries included in the study, the findings are presented and discussed in this section.



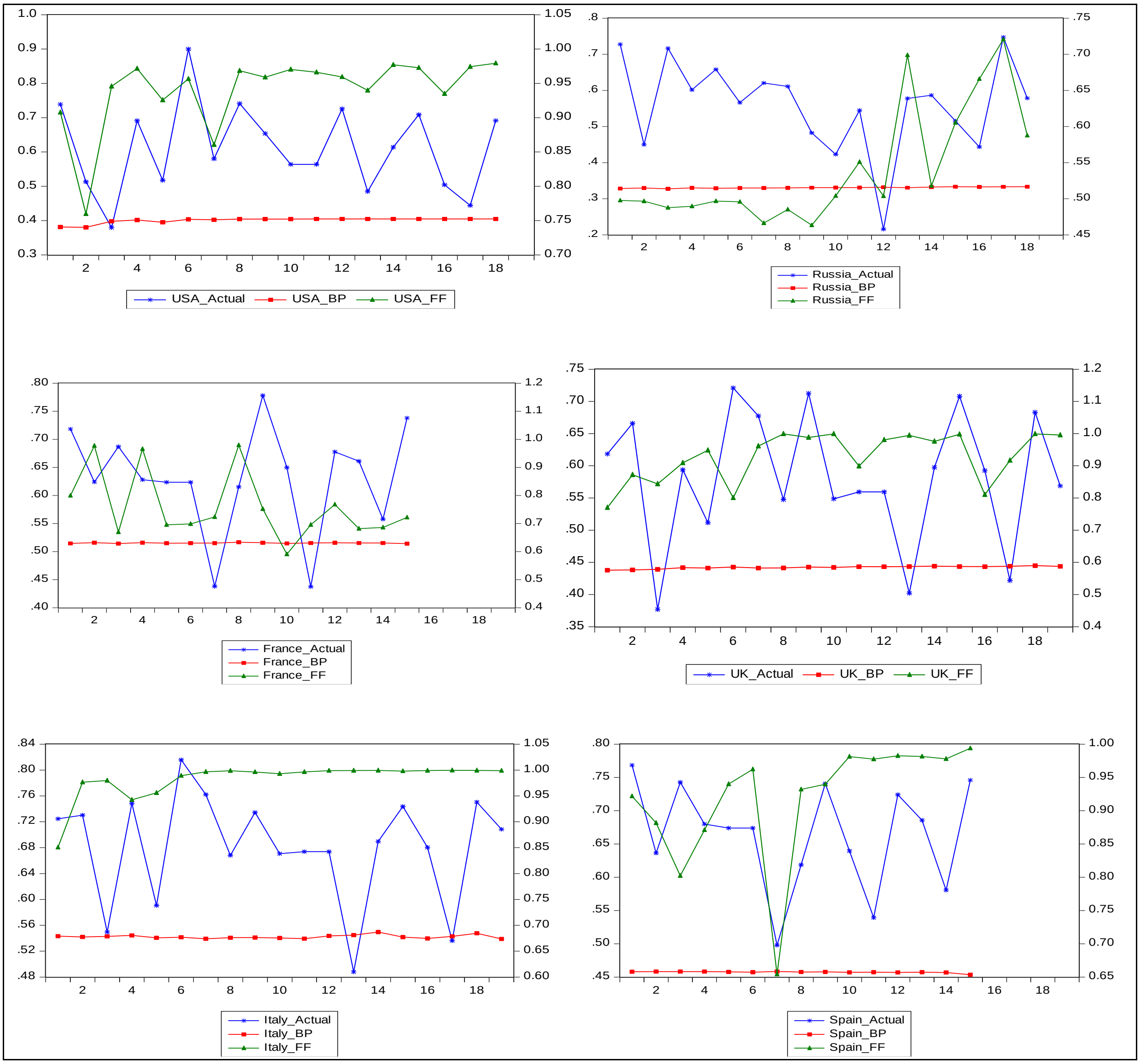


Figure 1. Actual Versus Predicted Share Returns

In panel 1, it is revealed that of the ten countries included in the study, the neural network proved to be more resilient in predicting the profitability of the stock markets in China and Brazil (see first two figures of panel 1). This is based on the fact that the plot of the anticipated values closely resembles the plot of the actual values for those countries, with the exception of a few instances where the predicted values have bigger spikes than the actual values. We should note that both the vertical and horizontal axes represent stock prices and timeframes. Two factors explain the disparity between horizontal and vertical values. First, the share prices and second, the starting period for each country differed.

The backward propagation (BP) network outperformed the feed-forward (FF) network in predicting the stock market profitability of the Brazilian economy; conversely, the feed-forward (FF) network outperformed the backward propagation (BP) in stock market profitability prediction in the case of the Chinese economy. Consequently, it could be concluded that by taking into account the dynamics of Covid19, the neural networks trained in this study have a strong prediction capacity of the profitability of the stock market in these countries. This finding implies that the Covid19 pandemic affects the profitability of the stock markets; therefore, to effectively predict the profitability of the stock market in these countries, there is the need to consider the dynamics of Covid19.

Germany, Russia, Turkey, and the United States are the next group of nations where the network has a moderate predictive power of the profitability of the stock market. Specifically for these countries, the neural network fared well in predicting profitability in certain periods but failed in others. For Germany and Turkey, it was discovered that the BP network was more robust, however, in the case of the United States and Russia, the FF network was found to perform better in its prediction abilities. For the first seven days, the FF network performed admirably in predicting the profitability of the stock market in the United States, but afterward, it performed poorly in its prediction. This is in contrast to Russia where the FF network predicted poorly initially only to become more reliable towards the end of the period. Concerning Germany and Turkey, the BP network appeared to be reliable in its prediction for a majority of the period under consideration, albeit with minor inaccuracies in the forecast.

In contrast, for countries such as France, Spain, Italy, and the United Kingdom, the neural network models tend to have poor predictive power. This is evident in the significant difference between the forecasted and actual profitability values. Although both the FF and BP networks had poor performance in predicting the profitability of the stock market in the case of these countries, the FF network was able to predict the profitability of the stock market more accurately in a few instances, particularly in the cases of France and the United Kingdom. Overall, the trained Neural Network model is unreliable in estimating the profitability of the stock market in these countries.

As a consequence of the findings, it could be inferred that the dynamics of Covid-19 play a role in projecting the profitability of the stock markets in China and Brazil; however, this cannot be true for the other nations included in the study. We can also infer that the stock markets in China and Brazil may be highly inefficient, possibly as a result of the presence of the Covid-19 shock, whereas the stock markets in countries such as Turkey, Germany, Russia, and the United States may be moderately inefficient, indicating the invalidity of the Efficient Market Hypothesis in the stocks during the sample period, and as a result, the stock market may be difficult to predict with linear models during the sample period. This is somewhat probable because of the indirect effect of Covid-19 on the stock market's performance, but it is also possible that the stock market responded poorly to the shocks as a result of the perception of investors and their reaction in terms of portfolio management.

Some of the other explanations include diverse agents' attitudes, noisy traders, variances in investment horizons, short sells, diversity in risk profiles, bid-ask spreads, herd behaviour, and market frictions. It is discovered that the majority of the stock market attitude could be termed as being bearish during the period under consideration. This presumption, on the other hand, may not hold for countries such as France, Spain, Italy, and the United Kingdom.

3. CONCLUSİON

This study employed the Artificial Neural Network models to predict the profitability of the stock market of the top ten most hit countries at the beginning of the pandemic. The models used are the Feed-Forward and Backward Propagation Neural Networks. When constructing and training the Neural Network models, the study took into consideration the dynamics of Covid-19-related death and infection. From the estimation result, it is discovered that taking into account the dynamics of Covid-19, the Neural Network models are effective in predicting the profitability of the stock market in China and Brazil signaling that the markets are inefficient. However, this is not the case with the stock markets in Germany, Russia, Turkey, and the United States where the profitability is only partly predicted accurately. Conversely, in the case of countries such as France, Spain, Italy, and the United Kingdom, there exists a significant difference between the actual and predicted profitability of the stock markets, indicating a poor predictive power of the Neural Network models and efficiency of the markets even in the face of the shock from the pandemic.

AUTHOR DECLARATIONS

Declarations of Research and Publication Ethics: This study has been prepared in accordance with scientific research and publication ethics.

Ethics Committee Approval: Since this research does not include analyzes that require ethics committee approval, it does not require ethics committee approval.

Author Contributions: All the authors contributed significantly to the development of the article.

Conflict of Interest: There is no conflict of interest arising from the study for the author or third parties.

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APPENDIX

Root Mean Square Errors and Accuracy of Measure

Table 1 Root Mean Square Errors and Accuracy of Measure

	Backward Propagation Model		Feed Forward Model	
Country	RMSE	Accuracy of measure	RMSE	Accuracy of measure
Russia	0.2502	0.9737	0.1722	0.9992
UK	0.0875	0.9952	NA	0.7887
Brazil	0.1645	0.9907	0.0237	0.9955
USA	NA	0.8871	NA	0.7450
Germany	NA	0.9609	NA	0.9350
Italy	0.1050	0.9999	NA	0.8592
Turkey	0.2170	NA	0.2248	NA
Spain	0.1165	0.9986	NA	0.8968
China	0.3634	0.9344	0.2689	0.9709
France	0.1342	0.9975	NA	0.9297

NA – Not available.