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Stock Price Forecasting for Jordan Insurance Companies Amid the COVID-19 Pandemic Utilizing Off-the-Shelf Technical Analysis Methods

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Abstract: One of the most difficult problems analysts and decision-makers may face is how to improve the forecasting and predicting of financial time series. However, several efforts were made to develop more accurate and reliable forecasting methods. The main purpose of this study is to use technical analysis methods to forecast Jordanian insurance companies and accordingly examine their performance during the COVID-19 pandemic. Several experiments were conducted on the daily stock prices of ten insurance companies, collected by the Amman Stock Exchange, to evaluate the selected technical analysis methods. The experimental results show that the non-parametric Exponential Decay Weighted Average (EDWA) has higher forecasting capabilities than some of the more popular forecasting strategies, such as Simple Moving Average, Weighted Moving Average, and Exponential Smoothing. As a result, we show that using EDWA to forecast the share price of insurance companies in Jordan is good practice. From a technical analysis perspective, our research also shows that the pandemic had different effects on different Jordanian insurance companies.

Keywords: financial time series forecasting; stock markets; forecasting methods; technical analysis

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1. Introduction

According to the Amman Stock Exchange (ASE), Jordan now has 20 insurance businesses listed, as well as several companies that have been liquidated owing to financial problems. This is a huge number for a small country such as Jordan, whose insurance market is relatively small compared to many of its regional peers, contributing to around 3% of the MENA region's gross written premiums. In particular, this is seen when compared to a much larger country such as Egypt, which only has 32 insurance companies, some of which are among the region's oldest (Oxford Business Group 2017). Only the Arab Orient Insurance Company (with a 16.5% share of gross premiums), Jordan Insurance (10.14%), and Middle East Insurance (7.35%) exceeded the 5% market share threshold in the first half of 2013, according to data from the Jordan Insurance Federation (JOIF), along with First Insurance claiming a share of 4.9% of the Jordanian market (Oxford Business Group 2017).

Despite the potential need for consolidation, the business has been devoid of mergers and acquisitions for more than two decades. Because the majority of the market is concentrated on third-party vehicle insurance, whose premiums are set by the government, merging two motor-focused companies to form a larger one makes no sense.

Furthermore, some companies have lacked the solvency margin since 2015, and they have neither been warned nor taken legal action to rectify the situation. Another big issue arises in the vehicle insurance market by bypassing or evading the concept of compulsory insurance; the victim is the citizen, who falls into the trap of some insurance brokers, while the reputation of the sector suffers as a result. Furthermore, the increase in the market share of some compulsory insurance companies in violation or circumvention of the instructions represents an increase in the number of insured citizens who will become potential victims of these companies' inability to fulfill their obligations to them, even if they have a solvency margin equal to or exceeding the minimum. It generates enough profit from its operations to offset losses resulting from compulsory insurance.

The challenge for insurers stems from the regulatory requirement that, in order to sell comprehensive coverage, companies must also provide third-party liability (TPL) coverage at a government-determined rate. TPL premiums are now low, according to the industry, and many insurers accept losses on this line of business, which they try to offset with more profitable comprehensive offers. As a result, technical outcomes are under pressure, which will persist if the industry faces structural challenges (Oxford Business Group 2020).

These challenges, among other things, resulted in financial losses and caused some insurance companies to be hesitant to pay claims, as well as harming the industry's reputation. After the COVID-19 pandemic in early 2020, the financial status of this industry will deteriorate much further. We will use technical analysis tools to forecast the share price of a randomly selected Jordan insurance company in order to shed light on their performance and determine which technical analysis tool is the best suited for forecasting.

Due to the instable and complex nature of such markets, data amount, high degree of ambiguity, noise, and the fact that they are always affected by numerous factors, forecasting the stock market and other traded financial instruments has always been a challenging task (Khan 2014; Agrawal et al. 2013; Ghatasheh et al. 2020). Stock market forecasting refers to the actions made to provide interested parties, such as investors and customers, with a predictable picture of the future direction and variation of the object price. Investors could make successful decisions or prevent losses if they could accurately forecast future stock prices (Singh et al. 2019, 2021; Sunny et al. 2020; Lin et al. 2020; Shynkevich et al. 2017; Mehta et al. 2021; Zhuo et al. 2021).

We argue that the choice of a technical analysis tool is governed by the ambiguity and subjectivity that surrounds determining the optimal time range for a predictor to consider when making a valid estimate. This is because there is no optimal time range and no consensus among analysts on what number of days, months, or years from a time series the forecaster should choose in order to make an acceptable and accurate forecasting. Choosing different periods may have an impact on the accuracy of forecasting and result in various outcomes. For example, we choose different periods of data for both well-known simple moving average (SMA), and weighted moving average (WMA) to forecast the price share of one of the insurance companies, namely Middle East Insurance. We evaluate the forecasting outcome using different error measures such as mean absolute error (MAE), mean percentage error (MPE), mean square error (MSE), tracking signal (TS), and mean absolute percent error (MAPE). Table 1 shows these pilot results.

As can be seen in Table 1, which shows that depending on the time range used (5, 10, 15 and 20 days), SMA and WMA showed different results. As a result, this could lead to incorrect stock price forecasts and thus poor investment decisions. For example, the errors in the results are higher when using 20 days than when using a period of 10 days. Accordingly, the significance of the time frame chosen, which is heavily dependent on personal experience, determines the stock's price prediction and accuracy. On the contrary, our EDWA will consider all available data points in a time series dataset.

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Table 1. The performance of SMA and WMA using the daily closing prices of Middle East Insurance inc. in 2020. Data obtained from Amman stock exchange (https://www.ase.com.jo/en/company_historical/MEIN, accessed on 1 November 2021). STD: standard deviation.

Method	Period (Days)	MAE	MAPE	MPE	MSE	TS
SMA	5	0.0463	0.0361	0.0068	0.0040	0.1509
	10	0.0498	0.0389	0.0105	0.0048	0.2234
	15	0.0476	0.0373	0.0124	0.0041	0.2895
	20	0.0480	0.0378	0.0147	0.0042	0.3471
	STD	0.0015	0.0012	0.0033	0.0003	0.0846
WMA	5	0.1078	0.0805	−0.0469	0.0988	−0.6131
	10	0.2188	0.1653	−0.1325	0.2450	−0.8179
	15	0.3284	0.2492	−0.2172	0.3899	−0.8830
	20	0.4395	0.3317	−0.2995	0.5437	−0.9124
	STD	0.1426	0.1082	0.1088	0.1911	0.1349

To avoid the time parameter, we contemplate our earlier nonparametric forecasting method (Altarawneh 2019; Hassanat et al. 2021), known as the Exponential Decay Weighted Average (EDWA), comparing it with other technical analysis tools, to predict the share price of Jordanian insurance companies, especially during the COVID-19 period, and see which is a viable tool for forecasting stock prices.

Basically, WMA and exponential smoothing approaches (ES) are both used to create the EDWA forecasting method. This method considers the entire time series as we argue that a technical analysis method that takes into account all data, not just some historical data points, is beneficial for forecasting in general, and for forecasting stock price of Jordanian insurance companies in particular, as these companies' challenges and problems have persisted for a long time.

Since the most recent share price is more relevant and important than previous prices, EDWA also weights it more heavily. However, this allows other factors to affect stock prices as we dig deeper into a time series. Therefore, we weight the current prices higher, which are influenced by current factors, such as the COVID-19 pandemic, while also giving lower weights to the older prices, which are influenced by older factors that are still influencing the stock price. It is worth noting that the literature confirms that no single method or model can 100% accurately assess and anticipate complex data patterns; in addition, a wide variety of economic and non-economic factors also influence stock markets (Agrawal et al. 2013; Santos 2011; Fikru 2019).

2. Related Literature

The random walk theory (Fama et al. 1969; Fama 1995), and the Efficient Market Hypothesis (Fama 1965) were used as primary models on which a variety of stock market prediction methodologies were built. On the other hand, investigations based on these models revealed that the price of a stock cannot be accurately forecast. Although the financial market is difficult, chaotic, unstable, nonlinear, and dynamic in nature, it can be anticipated with an accuracy of more than 50%, according to some empirical studies (Malkiel 2003; Prechter and Parker 2007; Bollen et al. 2011), and it does not follow the random walk model (Lo and MacKinlay 1988).

To forecast the stock's trend, a plethora of methodologies have been employed in the literature. Technical analysis, Fundamental analysis, and Machine learning methods are the three primary themes of prediction methodologies used.

Technical analysis is an approach employed to forecast the direction and movement of future stocks price and other traded securities, using solely the company's historical stock prices and trading volumes. In technical analysis, we look at the price data patterns that demonstrate continuations or setbacks in a stock market trend. Technical analysis encompasses numerous techniques, such as the simple moving average (SMA), exponential smoothing (ES), weighted moving average (WMA), Candlestick Agent, and others. In the financial field, most of the traditional techniques of stock price prediction use statistical methods, which were generated from historical data.

The approach of technical analysis is used extensively for predicting future stock prices based purely on the company's previous trading volumes and stock prices (Turner 2007; Chourmouziadis and Chatzoglou 2016). In technical analysis, we look at price data patterns to see if the stock market trend is continuing or reversing. SMA, ES, WMA, Candlestick Agent, and other approaches are all used in technical analysis. Most classic stock price prediction strategies in the financial world rely on statistical methodologies derived from past data (Park and Irwin 2007; Edwards et al. 2012; Nti et al. 2020).

The fundamental analysis approach, on the other hand, evaluates the company's intrinsic values based on an examination of its financial statements and economic indicators in order to forecast future stock prices, examples of such approach include (Chen and Chen 2013; Drakopoulou 2016; Chen et al. 2017; Abarbanell and Bushee 1997; Muhammad 2018).

Artificial neural networks and Genetic Algorithms among others are examples of tools and methodologies used in artificial intelligence research field to anticipate stock market movements. Many studies have looked into the benefits of using such approaches including and are not limited to (Nevasalmi 2020; Patel et al. 2015; Khan et al. 2020; Nabipour et al. 2020; Zhong and Enke 2019; Singh 2018; Chowdhury et al. 2020; Valencia et al. 2019). In addition to a slew of other studies attempting to build and discover new machine learning approaches, including (Qiu and Yu 2016; Narloch et al. 2019; Khashei and Hajirahimi 2018; Samer et al. 2018; Abadleh et al. 2021; Chi 2018). Artificial intelligence and Machine learning in particular are not just for prediction and forecasting; they are also employed in a variety of other areas such as Natural Language Processing (Alghamdi and Teahan 2017; Hassanat and Altarawneh 2014; Hassanat and Jassim 2010; Al-Shamaileh et al. 2019; Hassanat et al. 2015b, 2015c; Tarawneh et al. 2020a; Hassanat and Tarawneh 2016), Software engineering (Salman et al. 2018; Eyal Salman 2017; Eyal Salman et al. 2015), Internet of things (Mnasri et al. 2014, 2015, 2017a, 2017b, 2018a, 2018b, 2019, 2020; Abdallah et al. 2020a, 2020b; Tlili et al. 2021), Computer vision (AlTarawneh et al. 2017; Alqatawneh et al. 2019; Tarawneh et al. 2018, 2019a, 2019b, 2020b; Al-Btoush et al. 2019; Hassanat et al. 2015a, 2017a, 2017b, 2018a; Hassanat and Tarawneh 2016; Hassanat 2018e), Game theory (De Voogt et al. 2017; Hassanat et al. 2018b), Big data classification (Hassanat 2018a, 2018b, 2018c, 2018d, 2018e), Security Network and Anomaly Detection (Al-kasassbeh and Khairallah 2019; Al-Naymat et al. 2018; Zuraiq and Alkasassbeh 2019; Almseidin et al. 2019a, 2019b, 2019c; Abuzuraiq et al. 2020; Al-Kasassbeh et al. 2019; Almseidin et al. 2019c; Alothman et al. 2020; Rawashdeh et al. 2018; Alkasassbeh 2018; Hassanat et al. 2022). Security is a field that can benefit from machine learning techniques. Using a biometric key derived from machine learning models, it is possible to maintain a communication link between senders and receivers (Hamadaqa et al. 2019; Mulhem et al. 2019; Mars et al. 2019). Moreover, the use of machine learning can be applied to indoor localization and distance estimation (Alabadleh et al. 2018; Aljaafreh et al. 2017; Abadleh et al. 2016, 2017).

Forecasting practitioners, on the other hand, demonstrate the utility and application of technical analysis. This is particularly evident on financial websites and in newspapers that process financial and statistical data using technical analysis. Furthermore, in recent years, study on the profitability of technical analysis has expanded. For example, (Park and Irwin 2007) reviewed studies that investigated the potential profits provided by technical analysis. They discovered that technical analysis consistently generates profit in a variety of markets, including the stock and foreign currency markets.

According to (Mitra 2011), most technical trading techniques may reasonably capture the direction of market moves and provide considerable positive returns in both long and short positions. In another interesting study (Vasiliou et al. 2006), the Athens Stock Exchange was used to see how well simple technical analysis can forecast stock price fluctuations. This study looked into these consequences for the Athens market's most important index, the Athens General Index. Standard tests and bootstrap are among the approaches used for the evaluation. The findings support the technical analysis methods investigated.

Brock et al. (1992) conducted a seminal empirical study to prove technical analysis profitability. The same work was extended by (Ma 2022), comparing the profitabilities of using the official closing price vs. the last tick price, based on data from Hong Kong from 2011 to 2018, and the results suggest that using the last tick price rather than the official closing price improves profitability significantly using technical analysis methods.

Ausloos and Ivanova (2002) recalled the traditional technical analysis methods of stock evolution. Momentum indicators are used to predict the direction of a market trend and so provide signals before the trend changes. As a result, a typical technical analysis investing plan is sketched.

In his study, (Zulkarnain 2014) sought to see whether SMA technical analysis can be used to forecast top gainers' stock prices on the Indonesia Stock Exchange (IDX). He concluded that the difference between forecasted and actual prices is not significant. As a result, technical analysis is still a valuable tool for financial forecasting. (Wong et al. 2010) focused on the importance of technical analysis in determining when to enter and exit the stock market. The results show that the indicators used can achieve a high positive return. Singapore Stock Exchange (SES) member firms have been found to rely heavily on technical analysis, which has resulted in big profits. Hence, technical analysis seems to be an ideal approach to select some of its techniques and try to propose a new model based on it in order to improve the investor's predictive potential. Our EDWA falls into this forecast category.

3. Materials and Methods

The EDWA forecasting method is a mix of WMA and ES, but differs in the weighting and time period used. There is no specific time period here, as the method uses all available data starting with the current value up to day 1 and it gives a higher weight to the current value and the next value; this is similar to WMA but goes back to day 1. However, to emphasize the importance of the most recent values, we propose assigning a weight that is weighted twice as much as the previous value, so the method becomes almost similar to ES in terms of the weighting system.

EDWA usually assigns a certain initial weight to the final price, which is set to 2 by default, and this weight is reduced in half (exponential decrease) with each subsequent price. In other words, the current price is weighted with 2, the previous day weighted with 2/2, the previous day with 1/2 and so on up to day 1. This is why it is known as the exponentially decaying weighted average.

It is worth noting that if the time series is lengthy, the decaying weight may approach 0 due to the precision of floating point on today's computers. To get around this issue, EDWA applies the lowest weight possible to all deeper prices in the time series. The EDWA formula is as follows:

$$EDWA(t+1) = \frac{w_1 p_t + w_2 p_{t-1} + w_3 p_{t-2} + \cdots + w_n p_{t-n+1}}{w_1 + w_2 + w_3 + \cdots + w_n} \tag{1}$$

where $w_1 = 2, w_2 = \frac{w_1}{2}, w_3 = \frac{w_2}{2}, \ldots, w_n = \frac{w_{n-1}}{2}$, n is the number of days or prices in the time series, p_t is the current price, p_{t-1} is the previous price, and p_{t-n+1} is the oldest price.

The SMA is defined by

$$F_{n+1} = \frac{1}{k} \sum_{t=n}^{n-k} P_t$$

WMA is defined by

$$F_{n+1} = \frac{1}{k} \sum_{t=n}^{n-k} w_t * P_t$$

ES is defined by

$$F_{n+1} = a * P_t + (1-a) * F_t$$

where F_{n+1} is the forecasted value, P_t is the actual price of the share at time (day) t, k is the number of concerned days, w is the weighting factors and a is a smoothing constant.

To obtain the general trend of the share price of our sample study, we propose the use of the average of the averages of all periods, starting with the current price and going back by one day each time to obtain n averages, where n is the size of the time series, then we divide the sum of these averages by n, as formulated by

$$\text{Avgavg}(n+1) = \frac{\sum_{i=n}^{1}\left(\frac{\sum_{j=n}^{\mathrm{i}} \mathrm{P_j}}{n-i+1}\right)}{n} \tag{2}$$

where Avgavg(n + 1) is the forecasted price of a time series of size = n based on the average of the averages of all previous prices.

The chosen technical analysis methods, namely EDWA, SMA, WMA, and ES, were applied to the time series datasets of the Jordanian insurance companies for forecasting. These methods were compared based on their forecasting results. To measure the forecasting error of each method we opt for some of the well-known error indicators, namely MAE, MSE, MPE, MAPE, and TS (Lei 2017; Haji Rahimi and Khashei 2018).

Since all of these indicators are based on the forecasting error, we define the forecast error as

$$E(t) = P(t) - F(t)$$

where $E(t)$ is the forecasting error at time t (on our case day), $P(t)$ is the actual share price, and $F(t)$ is the forecasted price at the same t. Consequently, the Absolute forecasting error (AE) is defined by

$$AE(t) = |E(t)|$$

the Percent Error (PE) is defined by

$$PE(t) = \frac{E(t)}{P(t)}$$

and the Absolute Percent Error (APE) is defined by

$$APE(t) = \frac{AE(t)}{P(t)}$$

Accordingly, we can define the error measures of forecasting as

$$MAE = \frac{1}{n}\sum_{t=1}^{n} AE(t)$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n} E(t)^2$$

$$MPE = \frac{1}{n}\sum_{t=1}^{n} PE(t)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} APE(t)$$

and

$$TS = \frac{\frac{1}{n}\sum_{t=1}^{n} E(t)}{MAE}$$

where n is the number of forecasted prices, in this work, it is equal to the size of the time series minus 1, since we are going to forecast all prices from day 1 through day n (the current price) in order to be able to use a ground-Compare truth price to calculate forecast error.

To forecast the stock price of Jordanian insurance companies during COVID-19, we collected the daily closing prices of 10 Jordanian insurance companies, out of 20 insurance companies, because there was not enough publicly available data for the rest of the other 10 companies. The data were collected from the official website of the Amman Stock Exchange (https://www.ase.com.jo/, accessed on 1 November 2021). Such online systems' data sources are typically historical stock prices and/or technical indicators derived from a time series examination of stock prices (Chourmouziadis and Chatzoglou 2016; Kimoto et al. 1990; Qian and Rasheed 2007). The period of the prices of each company starts from January 2018 to November 2021. Thus, we covered two distinct periods: the COVID-19 pandemic period (2020–2021), and the non-pandemic period (2018–2019).

For the sake of simplicity, we restricted the data to the daily closing prices. Each time series consists of 51 to 220 closing prices, this is all available data retrieved from the official Amman Stock Exchange website for the past four years. Table 2 shows the 10 Jordanian insurance companies investigated in this study. Table 3 shows some basic statistics of the insurance companies chosen.

Table 2. Description of the study sample.

Company's Name	Symbol	Average Value Traded	Average No. of Trans	Listed Shares	Available Data (Days)
Middle East Insurance	MEIN	37,853.6	3.1	22,050,000	144
Al-Nisr Al-Arabi Insurance	AAIN	2355.4	1.6	10,000,000	111
Jordan Insurance	JOIN	8144.8	3.7	30,000,000	143
Arabia Insurance Company-Jordan	AICJ	2425.5	2.5	8,000,000	178
Delta Insurance	DICL	3931.5	2.2	8,000,000	142
Jerusalem Insurance	JERY	1780.1	1.8	8,000,000	57
The United Insurance	UNIN	10,320.0	1.9	8,000,000	51
Jordan French Insurance	JOFR	3165.5	2.1	9,100,000	220
Al-Manara Insurance Plc.Co.	ARSI	30,751.92	2.95	5,600,000	147
Arab Orient Insurance Company	AOIC	1748.47	2.75	21,438,252	168

Table 3. Basic statistics of the study sample. All prices in Jordan Dinar.

Company	Market Capitalization	High Price	Low Price	Closing Price	Average Price	Value Traded	Turnover Ratio	Dividend	EPS
MEIN	22,050,000	1.45	1.13	1.28	1	6,795,941	24	0.050	0.046
AAIN	10,000,000	5	4	4	4	246,972	1	0.300	0.306
JOIN	30,000,000	2.33	1.1	1.42	1.44	478,096	1.11	0.000	0.100
AICJ	8,000,000	1	1	1	1	1,425,692	20	0.000	0.078
DICL	8,000,000	1	1	1	1	30,124	0	0.050	0.076
JERY	8,000,000	2	2	2	2	19,067	0	0.070	0.156
UNIN	8,000,000	1	1	1	1	282,431	3	0.100	0.188
JOFR	9,100,000	1	1	1	1	59,437	1	0.000	0.100
ARSI	5,600,000	1	0	0	0	194,495	8	0.000	0.317
AOIC	25,438,252	1.63	1.14	1.55	1	66,046	0	0.000	0.265

4. Results and Discussion

For the forecast, the chosen technical analysis methods EDWA, SMA, WMA, and ES were first applied to one of the time series datasets of the Jordanian insurance companies, namely MEIN. Figures 1–4 illustrate the forecast results for each method.

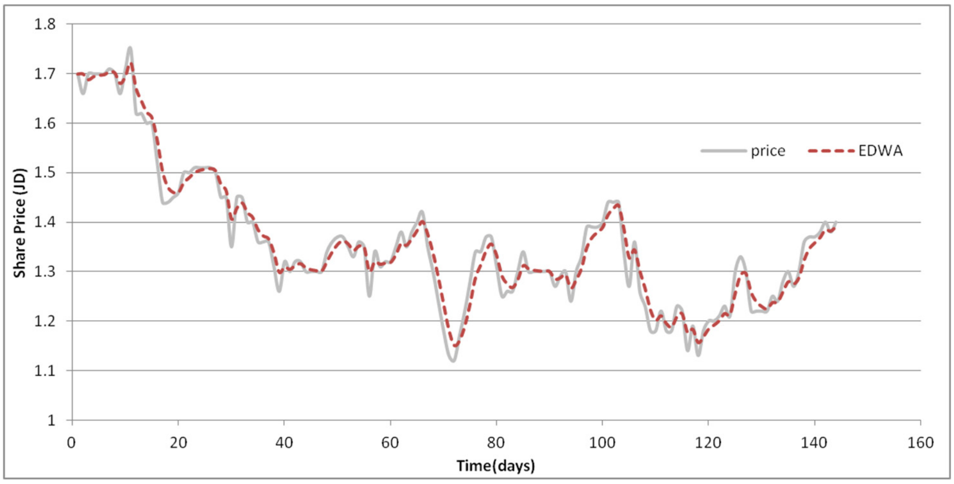

Figure 1. Forecasting results of MEIN using EDWA.

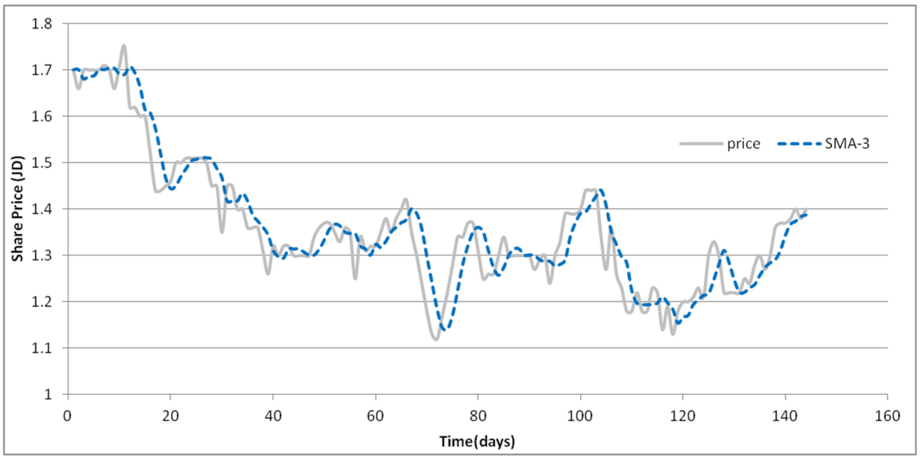

Figure 2. Forecasting results of MEIN using SMA on 3 days period.

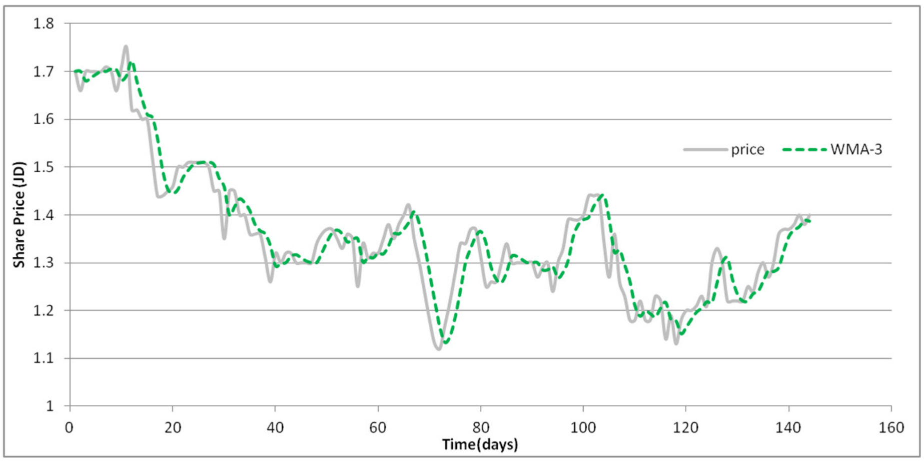

Figure 3. Forecasting results of MEIN using WMA on 3 days period.

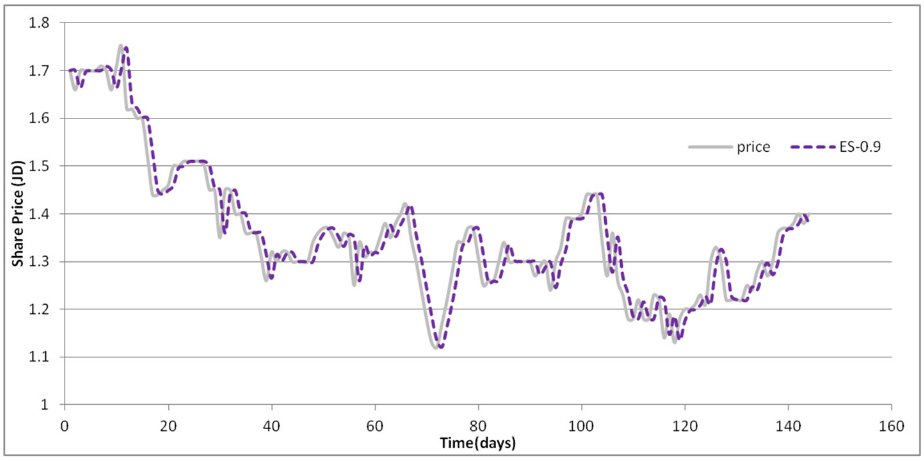

Figure 4. Forecasting results of MEIN using ES, with alpha = 0.9.

If we examine the curves in Figures 1–4, we can see that both EDWA and ES have significantly higher forecasting performance than SMA and WMA. Perhaps such a solid performance is due to the inclusion of all prices in the time series that both EDWA and ES enable. Although both SMA and WMA used only three days more, the outcomes were not comparable. However, to support this conclusion, we need to apply these approaches to of the all Jordanian insurance companies' datasets, gather measures of error for a fair comparison, and determine which technical analysis methods are most suited to our data. Tables 4–6 show the measures of error after forecasting all 10 datasets using the four technical analysis methods.

Table 4. Forecast errors of technical analysis methods on MEIN, AAIN, JOIN, and AICJ. Bold values signify the minimum error.

CN	Method	MAE	MAPE	MPE	MSE	TS	CN	Method	MAE	MAPE	MPE	MSE	TS
	EDWMA	**0.018**	**0.014**	**0.002**	**0.001**	0.125		EDWMA	**0.021**	**0.005**	**−0.001**	**0.002**	−0.189
	SMA-3	0.038	0.029	0.004	0.003	0.11		SMA-3	0.044	0.011	−0.002	0.007	−0.184
	WMA-3	0.047	0.033	−0.004	0.022	−0.174		WMA-3	0.074	0.018	−0.01	0.15	−0.577
	ES-0.1	0.062	0.047	0.021	0.006	0.423		ES-0.1	0.114	0.028	−0.005	0.023	−0.235
	ES-0.5	0.036	0.027	0.004	0.002	0.119		ES-0.5	0.043	0.011	−0.002	0.006	−0.189
MEIN	ES-0.9	0.03	0.023	0.002	0.002	**0.077**	AAIN	ES-0.9	0.028	0.007	**−0.001**	0.005	**−0.172**
	SMA-10	0.056	0.042	0.01	0.006	0.216		SMA-10	0.097	0.024	−0.004	0.017	−0.212
	WMA-10	0.142	0.091	−0.048	0.164	−0.602		WMA-10	0.362	0.09	−0.075	1.172	−0.839
	SMA-20	0.071	0.053	0.021	0.008	0.37		SMA-20	0.762	0.186	−0.165	2.74	−0.893
	WMA-20	0.252	0.164	−0.116	0.332	−0.761		WMA-20	0.762	0.186	−0.165	2.74	−0.893
	EDWMA	**0.034**	**0.019**	**0**	**0.003**	−0.059		EDWMA	**0.008**	**0.013**	**0.002**	**0**	0.096
	SMA-3	0.071	0.04	**0**	0.012	−0.055		SMA-3	0.016	0.028	0.003	**0**	0.106
	WMA-3	0.072	0.041	−0.007	0.026	−0.197		WMA-3	0.019	0.031	−0.003	0.004	−0.148
	ES-0.1	0.207	0.121	0.016	0.086	−0.079		ES-0.1	0.03	0.051	0.014	0.001	0.243
JOIN	ES-0.5	0.068	0.038	**0**	0.011	−0.059	AICJ	ES-0.5	0.016	0.027	0.003	**0**	0.107
	ES-0.9	0.045	0.026	−0.001	0.005	**−0.048**		ES-0.9	0.014	0.023	0.002	**0**	**0.069**
	SMA-10	0.154	0.086	0.004	0.057	−0.076		SMA-10	0.027	0.045	0.009	0.001	0.163
	WMA-10	0.205	0.122	−0.055	0.168	−0.466		WMA-10	0.053	0.081	−0.04	0.024	−0.565
	SMA-20	0.25	0.143	0.013	0.135	−0.1		SMA-20	0.034	0.058	0.013	0.002	0.191
	WMA-20	0.383	0.23	−0.118	0.394	−0.56		WMA-20	0.091	0.143	−0.099	0.045	−0.734

Table 5. Forecast errors of technical analysis methods on DICL, JOFR, JERY and UNIN. Bold values signify the minimum error.

CN	Method	MAE	MAPE	MPE	MSE	TS	CN	Method	MAE	MAPE	MPE	MSE	TS
DICL	EDWMA	**0.057**	**0.028**	0.013	**0.013**	0.393	JOFR	EDWMA	**0.01**	**0.012**	**0.001**	**0**	0.015
	SMA-3	0.124	0.06	0.026	0.059	0.364		SMA-3	0.022	0.026	0.001	0.001	0.012
	WMA-3	0.141	0.059	0.015	0.202	**0.046**		WMA-3	0.025	0.028	−0.003	0.005	−0.166
	ES-0.1	0.326	0.183	0.14	0.198	0.688		ES-0.1	0.037	0.042	0.004	0.002	0.023
	ES-0.5	0.114	0.056	0.026	0.05	0.396		ES-0.5	0.02	0.023	0.001	0.001	0.013
	ES-0.9	0.091	0.042	0.014	0.036	0.276		ES-0.9	0.018	0.021	0.001	0.001	**0.008**
	SMA-10	0.241	0.127	0.076	0.147	0.538		SMA-10	0.029	0.033	0.002	0.002	0.026
	WMA-10	0.443	0.152	**−0.001**	1.334	−0.376		WMA-10	0.061	0.065	−0.034	0.036	−0.571
	SMA-20	0.39	0.217	0.147	0.277	0.626		SMA-20	0.041	0.047	0.005	0.003	0.045
	WMA-20	0.705	0.263	−0.045	2.028	−0.526		WMA-20	0.113	0.118	−0.077	0.083	−0.699
JERY	EDWMA	**0.019**	**0.012**	**0.001**	**0.001**	0.015	UNIN	EDWMA	**0.026**	**0.022**	0.008	**0.001**	0.391
	SMA-3	0.042	0.026	0.001	0.003	0.017		SMA-3	0.054	0.045	0.016	0.004	0.35
	WMA-3	0.067	0.041	−0.016	0.053	−0.432		WMA-3	0.08	0.06	**−0.006**	0.055	**−0.182**
	ES-0.1	0.049	0.031	0.005	0.005	0.127		ES-0.1	0.117	0.1	0.082	0.02	0.816
	ES-0.5	0.039	0.024	0.001	0.003	0.02		ES-0.5	0.051	0.042	0.016	0.004	0.376
	ES-0.9	0.031	0.019	0.001	0.003	0.018		ES-0.9	0.046	0.038	0.009	0.003	0.24
	SMA-10	0.053	0.032	0.002	0.004	0.021		SMA-10	0.082	0.069	0.038	0.011	0.543
	WMA-10	0.278	0.167	−0.14	0.397	−0.848		WMA-10	0.276	0.202	−0.139	0.328	−0.744
	SMA-20	0.057	0.035	0.002	0.006	**0.002**		SMA-20	0.112	0.096	0.068	0.018	0.703
	WMA-20	0.551	0.336	−0.32	0.856	−0.956		WMA-20	0.489	0.386	−0.347	0.59	−0.912

Table 6. Forecast errors of technical analysis methods on ARSI and AOIC. Bold values signify the minimum error.

CN	Method	MAE	MAPE	MPE	MSE	TS	CN	Method	MAE	MAPE	MPE	MSE	TS
ARSI	EDWMA	**0.009**	**0.019**	**0**	**0**	−0.019	AOIC	EDWMA	**0.019**	**0.017**	**−0.002**	**0.001**	−0.161
	SMA-3	0.019	0.041	0.001	0.001	−0.018		SMA-3	0.039	0.036	−0.004	0.002	−0.152
	WMA-3	0.019	0.042	−0.007	0.001	−0.161		WMA-3	0.041	0.039	−0.009	0.007	−0.268
	ES-0.1	0.033	0.071	0.002	0.002	−0.078		ES-0.1	0.071	0.065	−0.011	0.008	−0.28
	ES-0.5	0.017	0.037	0.001	**0**	−0.02		ES-0.5	0.037	0.034	−0.003	0.002	−0.157
	ES-0.9	0.013	0.028	**0**	**0**	**−0.012**		ES-0.9	0.031	0.028	−0.002	0.001	**−0.117**
	SMA-10	0.031	0.068	0.001	0.002	−0.061		SMA-10	0.066	0.06	−0.008	0.006	−0.217
	WMA-10	0.044	0.108	−0.057	0.008	−0.497		WMA-10	0.093	0.093	−0.057	0.042	−0.602
	SMA-20	0.039	0.083	−0.002	0.003	−0.12		SMA-20	0.084	0.077	−0.015	0.011	−0.303
	WMA-20	0.074	0.183	−0.124	0.019	−0.658		WMA-20	0.159	0.166	−0.123	0.09	−0.733

Interestingly, EDWMA scored the fewest errors of the most commonly used error indicators, followed by ES when a = 0.09 was used, as can be seen in Tables 4–6. Even when SMA and WMA were used at various time intervals, both EDWMA and ES methods perform much better in terms of few errors and highly accurate forecasting. If the TS error indicator is major concern, the ES outperforms almost all methods, although the error difference is not significant when compared to EDWMA. These findings confirm our contention that it is better to incorporate all historical data when using a technical analysis tool.

ES appears to favor a certain value (a = 0.9) (Chopra and Meindl 2013; Paul 2011), and hence requires parameter adjustment before being used in practice, whereas EDWMA is a non-parametric technique that does not require parameter input prior to the forecasting process. The EDWMA provides good forecasting for Jordanian insurance companies because it is a non-parametric method that outperforms all other methods on all datasets as shown by most error measures used.

We looked at the use of EDWMA and ES for forecasting share prices before and after the pandemic because they were the top forecasters. Tables 7 and 8 show the forecasting results.

Table 7. Forecast errors of EDWNA and ES on data from all companies tested before the pandemic. Bold values signify the minimum error within this table, and highlighted values signify the minimum error between Tables 7 and 8.

CN	Method	MAE	MAPE	MPE	MSE	TS	CN	Method	MAE	MAPE	MPE	MSE	TS
MEIN	EDWMA	0.018	**0.014**	**0.002**	**0.001**	0.125	AAIN	EDWMA	**0.017**	**0.004**	**0.001**	**0.001**	0.247
	ES-0.9	**0.007**	0.027	0.019	0.005	**0.002**		ES-0.9	0.024	0.006	**0.001**	0.004	**0.196**
JOIN	EDWMA	**0.029**	**0.013**	**−0.009**	**0.002**	−0.696	AICJ	EDWMA	**0.009**	**0.015**	**0.003**	**0.000**	0.153
	ES-0.9	0.036	0.017	−0.011	0.003	−0.630		SMA-3	0.016	0.025	0.003	**0.000**	**0.116**
DICL	EDWMA	**0.013**	**0.015**	**0.007**	**0.000**	0.447	JOFR	EDWMA	**0.007**	**0.009**	**0.002**	**0.000**	0.200
	ES-0.9	0.018	0.020	**0.007**	0.001	**0.302**		SMA-3	0.013	0.016	0.002	**0.000**	**0.120**
JERY	EDWMA	**0.020**	**0.013**	**0.003**	**0.001**	0.192	UNIN	EDWMA	**0.032**	**0.025**	**0.016**	**0.002**	0.629
	ES-0.9	0.036	0.022	0.004	0.003	**0.144**		SMA-3	0.054	0.043	**0.016**	0.005	**0.370**
ARSI	EDWMA	**0.010**	**0.022**	**0.000**	**0.000**	−0.041	AOIC	EDWMA	**0.018**	**0.018**	**−0.001**	**0.000**	−0.080
	ES-0.9	0.014	0.032	**0.000**	**0.000**	**−0.035**		SMA-3	0.031	0.030	**−0.001**	0.001	**−0.051**

Table 8. Forecast errors of EDWMA and ES on data from all companies tested after the pandemic. Bold values signify the minimum error within this table, and highlighted values signify the minimum error between Tables 7 and 8.

CN	Method	MAE	MAPE	MPE	MSE	TS	CN	Method	MAE	MAPE	MPE	MSE	TS
MEIN	EDWMA	0.019	**0.015**	**0.001**	**0.001**	0.052	AAIN	EDWMA	**0.022**	**0.005**	**−0.002**	**0.002**	−0.509
	ES-0.9	**0.001**	0.032	0.025	**0.001**	**0.002**		ES-0.9	0.028	0.007	−0.003	0.004	**−0.467**
JOIN	EDWMA	**0.034**	**0.021**	**0.004**	**0.003**	0.195	AICJ	EDWMA	**0.007**	**0.012**	**0.001**	**0.000**	0.048
	ES-0.9	0.047	0.030	**0.004**	0.005	**0.158**		SMA-3	0.012	0.021	**0.001**	**0.000**	**0.028**
DICL	EDWMA	**0.022**	**0.020**	**−0.007**	**0.001**	−0.384	JOFR	EDWMA	**0.015**	**0.016**	**−0.001**	**0.000**	−0.083
	ES-0.9	0.035	0.031	**−0.007**	0.002	**−0.245**		SMA-3	0.026	0.029	**−0.001**	0.001	**−0.061**
JERY	EDWMA	**0.017**	**0.010**	**−0.003**	**0.001**	−0.292	UNIN	EDWMA	**0.021**	**0.019**	**0.004**	**0.001**	0.154
	ES-0.9	0.026	0.015	**−0.003**	0.002	**−0.203**		SMA-3	0.034	0.031	**0.004**	0.002	**0.102**
ARSI	EDWMA	**0.007**	**0.014**	**0.001**	**0.000**	0.069	AOIC	EDWMA	**0.019**	**0.016**	**−0.003**	**0.001**	−0.248
	ES-0.9	0.010	0.021	0.002	**0.000**	**0.068**		SMA-3	0.030	0.025	−0.004	**0.001**	**−0.198**

Tables 7 and 8 show that both EDWMA and ES have good forecasting performance on insurance company price shares both before and after the pandemic. This demonstrates that technical analysis approaches are a suitable fit for such scenarios, and this finding is consistent with earlier research (Wong et al. 2010; Taylor and Allen 1992; Mitra 2011; Ausloos and Ivanova 2002; Vasiliou et al. 2006; Ma 2022), for example.

It is worth noticing that the EDWMA performed better before and after the epidemic on most datasets. Another interesting observation is the forecasting error before and after the pandemic. We can see that forecasting errors for some companies, such as JERY, ARSI, AICJ, UNIN, and MEIN decreased after the pandemic. This could be due to the nature of stock prices being more predictable after the major effect of the pandemic.

Other companies, such as DICL, AAIN, and AOIC, on the other hand, have marginally better forecasting outcomes prior to the pandemic. Additionally, two companies, JOIN and JOFR, demonstrate no substantial difference in forecasting performance before and after the pandemic. As a result, we cannot generalize the impact of the COVID-19 pandemic on Jordan's insurance business in terms of forecasting results (before and after) because each company has its own set of conditions.

To investigate the trend of the share prices of the selected Jordanian insurance companies, we applied the proposed Avgavg equation. The results of the trends are shown in Figure 5.

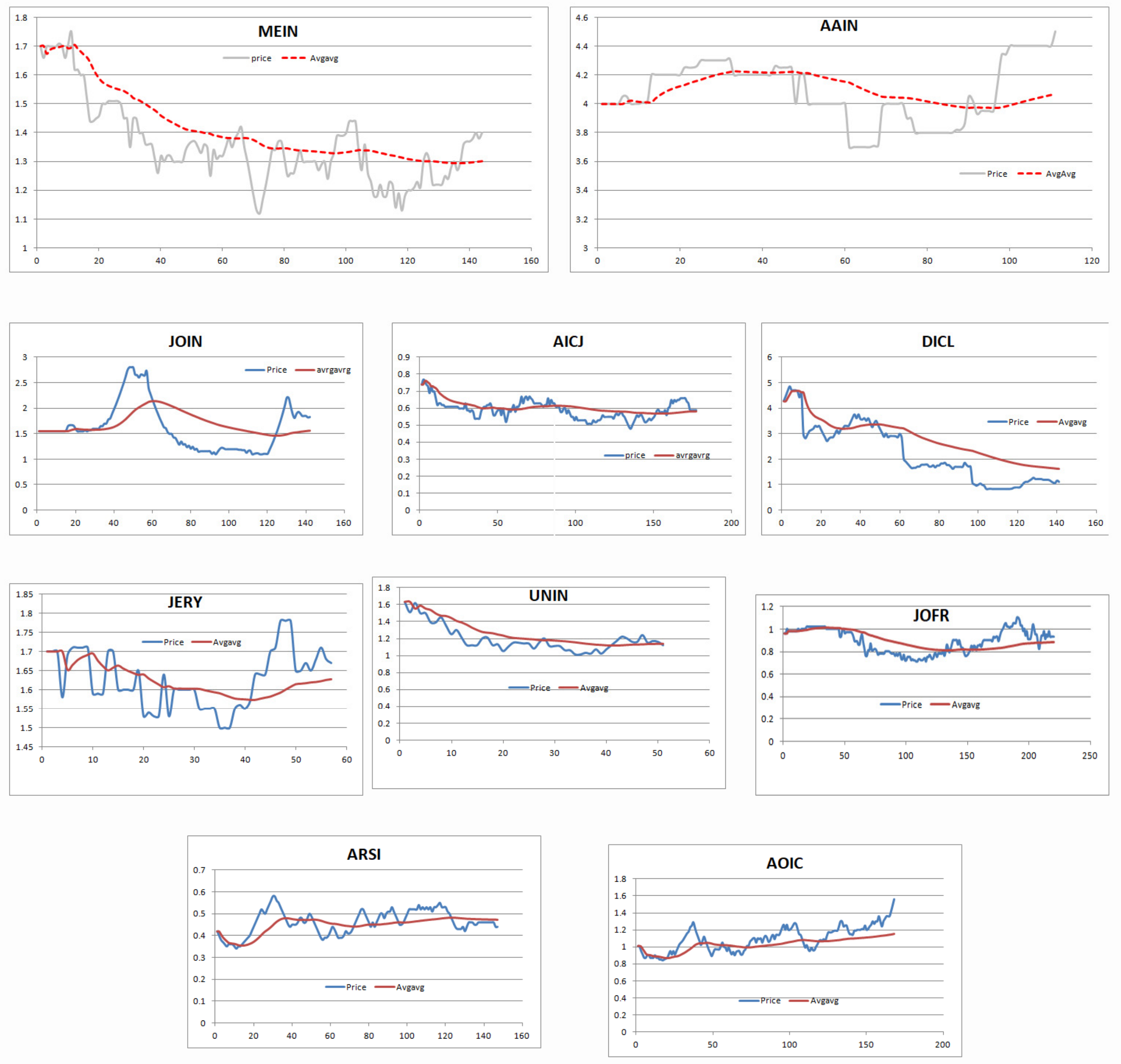

Figure 5. Avgavg trends approximation of share prices.

As shown in Figure 5, the Avgavg closely approximates share price trends. Most insurance companies started with a higher share price before the pandemic, which means that the pandemic partially hit the majority of the insurance companies surveyed. AOIC, on the other hand, is on a steady upward trajectory. Perhaps they found solutions to deal with the pandemic, or even profited from it. Additionally, if not increasing them, most companies stopped their share prices from falling, as they weathered the pandemic.

5. Conclusions

In this study, we used several technical analysis tools to forecast the share prices of a random sample of Jordanian insurance companies and examine their performance during the COVID-19 pandemic. The technical analysis tools used include parametric methods, namely SMA, WMA, ES, and one non-parametric method, our EDWMA, in addition to our trend approximation method, the Avgavg.

The experiments, which were conducted on the share prices of 10 Jordanian insurance companies, evaluated the forecasting performance against a range of error measures, including MAE, MAPE, MPE, MSE, and TS. The forecast results show that our EDWMA, followed by ES, are the best performers because of their reliance on all the historical prices. In contrast to EDWMA, the results show that the parametric methods must first be tuned before they can be used. This makes EDWMA the best choice for forecasting the datasets used. Moreover, the Avgavg interestingly exhibits the trends of the share prices of the analyzed companies and shows their performance in relation to the share prices before and after the COVID-19 pandemic.

The study has two limitations. First, due to a lack of publicly available data, the number of insurance companies tested was limited to ten, which represents half of the current insurance companies in Jordan. Second, we only employed a few common technical analysis approaches, ignoring a vast number of cutting-edge machine learning methods, such as deep learning forecasting methods. Our future research will concentrate on overcoming both limitations, particularly by integrating EDWMA with deep learning, as well as looking into more financial sectors.

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