Predicting Systematic Risk Using Artificial Neural Networks

A research proposal submitted to the faculty of Commerce, Law, and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in Finance and Investments.

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ABSTRACT

Financial institutions and investors are always investigating mathematical models that can enable them to make accurate predictions of time varying variables. For the longest time, statistical and autoregressive models have been at the forefront of forecasting. However, these are only accurate in short horizons; that is, these models are more accurate in daily, weekly, and monthly forecasts. This paper seeks to investigate long-horizon (yearly) forecasts using machine learning models called Artificial Neural Networks. The network uses neurons similar to biological neurons in living things, allowing them to study complex data patterns and retain pattern behaviors that allow them to make accurate predictions.

The paper is based on the novel discovery that in forecasting long-horizon time series data, neural networks outperform statistical models significantly. The paper uses market data from the Johannesburg Stock Exchange and the New York Stock Exchange to represent the emerging and advanced markets, respectively. The forecasted data involves pre and post COVID-19. The shock introduced by the coronavirus is investigated to check if the forecasting ability of the model is affected.

The empirical results demonstrate that the models accurately forecast systematic risk in the South African market more than in the American market. The accuracy of the model is measured by using root mean square error and mean absolute error. The model produced low error values for both markets, indicating their effectiveness in forecasting. It was expected that the error measures would consistently get lower as the time horizon increased; however, there were inconsistencies. For a portfolio manager, the results obtained in this research are interesting because the model handles large quantities of data and forecasts long-horizon systematic risk with little error. However, further investigation on this model still needs to be done.

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1. Introduction

1.1 Background

Investors are rational and want to maximize returns at the lowest investment risk. Therefore, risk management has become an integral part of investments. There are two types of risk that are borne with investing: unsystematic risk and systematic risk (Abonongo et al., 2017). Unsystematic risk is the risk facing a particular stock of a certain company; its genesis may stem from the management process of the firm, leverage, and/or operational risk of a firm (Berk and Tutarli, 2020). It is mitigated through the process of diversification, which is the inclusion of uncorrelated stocks in the same portfolio (Puspitaningtyas, 2017). Should a certain company's stock collapse due to strikes or lawsuits, the other stocks in the portfolio of different companies can thrive, and fewer losses are incurred (Phuoc et al., 2018). Another type of risk is systematic risk, which is associated with the return on all stocks in relation to changes in the market (Sunchalin et al., 2019). The securities in the portfolio are exposed to changes in the financial market, such as interest rate rise and inflation (Phuoc et al., 2018).

However, Systematic risk cannot be mitigated by holding securities in different industries. Hence, it is the risk investors are willing to trade-off for a particular return rate on their investment (Puspitaningtyas, 2017). Systematic risk is crucial to financial institutions and policymakers. It has been used to estimate the performance of the stock market, which can be used as a barometer for the economy of a country (Challa et al., 2018). The capital asset pricing model has been used in evaluating the discounted cash flows on investment by estimating the security's return, the market return, and the systematic risk represented as beta (Hossain, 2019). Beta is defined as the covariance between securities return and the market return in proportion to the market return variances (Abonongo et al., 2017). Therefore, when the beta value is one, the security moves in the same direction as the market. Stocks with values above one are considered aggressive (riskier) than the market index, and those lower are defensive stocks, and risk-averse investors invest in these assets.

1.2 Research Gap

Beta is useful in stock valuation, asset pricing, cost of equity prediction, and portfolio management. Due to its broad applicability, it is forecasted to create better positions against risk. However, only short-term (daily and monthly) beta values have been estimated with some form of accuracy in the past. Long-term beta values have not been forecasted accurately. Systematic risk value has been predicted either using data driven filters such as a sample in estimates of Fama and MacBeth (1973), autoregressive models or demonstrating a parametric regression between beta and macroeconomic factors such as inflation and announcements of changes in interest rates (Ibrushi, 2014). Wu and Levees (2013) estimated constant monthly beta values using high-frequency data in the Fama and MacBeth model of up to 80 months to find the constant monthly beta values (Cenesizoglu et al., 2013).

In addition, Ordinary Least squares (OLS) together with Least-Trimmed Squares (LTS) and the Maximum hood type M-estimator (MM estimator) have been used to predict beta values at a specific point in time (Phuoc et al., 2018). Financial information of firms has also been important in estimating risk. Liquidity, financial leverage, profitability, operating efficiency, and a firm's size are used as independent variables, and beta is the dependent variable in finding beta at a specific time in a company. Upon conducting research, firm size was found to be the biggest influencer of beta (Bui et al., 2017). It is not the most accurate way of estimating beta due to different accounting methods of measuring the mentioned variables (Bui et al., 2017). The Autoregressive integrated moving average model (Arima) has been used in forecasting long-horizon systematic risk. Challa et al. (2018) employed Arima models to determine the stocks to include in the portfolio for investors with different risk aversion. The results indicated a lot of uncertainties for long term periods and fewer uncertainties for short term periods (Chala et al., 2018).

This research, therefore, aims to contribute to the long-horizon beta estimation for both emerging and advanced markets.

1.3 Research Objective

This paper aims to forecast long-horizon beta values to improve portfolio management and lower rebalancing costs. When portfolio managers have a better view of an asset's risk further into the future, a better strategy can be utilized for asset allocation in the portfolio. Managers can then distribute the right mix of assets according to the risk tolerance of the managed investment fund. For example, more stable assets can be added to a pension fund if the market is estimated to be riskier in the near future. The investigations are done in both emerging and advanced markets during stable and unstable environments. The aim is to assist managers in both markets, with different factors affecting time series stock data, and to find a universal model that can forecast risk with some accuracy.

This long horizon portfolio risk forecast is based on a novel discovery by Bou-Hamad and Jamali (2020) that in forecasting financial-time series data, data mining techniques outperform autoregressive models in long-horizon forecasts (high persistence in the mean equation). That is, data mining techniques are better at forecasting yearly returns than forecasting daily returns. These new models have been proven to offer better estimation results and have a few advantages, such as the ability to approximate any functional form that best describes data (Hill et al., 1993) from simple linear functions to complex functional forms. This property allows ANNs model to extract signals from complex data (Hill et al., 1993). ANNs structure design is similar to that of biological neurons, which means that once these networks learn data patterns, they predict accordance with the learned information (Krenker et al., 2011).

1.4 Research questions

The study aims to predict the future values of beta stocks for a 1-year horizon for both the emerging and developed markets to achieve better portfolio positions.

1) How do the emerging market forecast beta values compare to the developed market beta?

2) How accurate are the beta values estimations during market shocks such as COVID-19?

1.5 Contribution to the study

There is a rise in high volumes, velocity, and variety of data in financial institutions that has been recorded over the years (Alexander et al., 2017). This has led to a phenomenon of financial technology (fintech). The use of technology in financial institutions such as banking is advantageous. Inefficient, traditional models are eliminated, and more efficient machine learning techniques are used to lower costs and deliver quality service in a timely fashion (Philippon, 2017). Using ANNs in systematic forecasting improves models used in risk predictions in large, big data organizations. Stein's (2013) study of 'aligning models and data for systemic risk analyses' argues that the use of aggregated data models could have estimated the crash of the house market in 2007. Data is useful in providing informative decision making (Alexander et al., 2017); this research also aims to use the ANN's ability to study trends from historical data to forecast systematic risk for emerging and advanced markets.

In addition, this paper aims to contribute to the use of ANNs models over statistical methods that have been used over time in prediction studies. Statistical methods require data to be described in a certain functional form to utilize it in modelling accurately. ANNs can operate on continuous, discrete, and binomial data easily, and they are also able to use incomplete data that consists of trials and errors and data that is not described by any functional form (Colbourn and Rowe, 2005). This is very important since data in financial institutions has been recorded arbitrarily without following a certain pattern, and this has also been recognized as a major issue in big data management.

1.6 Significance of the Study

This research aims to predict monthly, quarterly, and yearly beta values accurately; this will allow portfolio managers to lower rebalancing costs that would otherwise be incurred if only short-term estimates were made. The increase in time horizon is to monitor the accuracy of the model as long-horizon systematic risk forecasts are made. The accuracy of the model is measured in both the emerging and advanced markets. In addition, the forecast is done when the macro-economic environment is stable and when shocks are introduced to the macro-economic environment. The positive results from this research will make it easy for managers to forecast the beta values and have enough time to hedge against risk. Managers will be able to allocate different asset classes in their portfolios according to their risk appetite.

1.7 Structure of the report

Firstly, the introduction is constructed, and a literature review follows; and this entails the latest research that has been achieved about systematic risk and the advancements that have been made in Artificial Neural Networks forecasting. An overview of how these technological techniques might be applied in anticipating risk will be proposed. In addition, the methodology follows and details the procedure on how the research will be conducted, the data, the sample size of the data used, the mathematical functions, and the soft packages used. In the results section, findings will be tabulated and explained further in the discussion, where the findings are assessed if an advancement has been made. Research questions should be answered for successful findings. Lastly, a conclusion will be made on the overall report.

2. Literature review

2.1 Theoretical Literature review.

Portfolio managers are looking to make returns on investments and, therefore, analyze the market to put themselves in better positions to take advantage of any arbitrage in the market. A rational investor maximizes returns by contemplating the time of investing, the type of securities to invest in, the profitability of the investment, and the risk associated with investing (Sarraj and Mabrouk, 2021). Therefore, any negative deviation from the expected return rate is a risk to the investor. The expected rate of return on a portfolio is a function of risk and is categorized into systematic and unsystematic risk (Chakrabarti and Das, 2021). Unsystematic risk is the risk unique to a firm due to the management style of the firm. It is reduced through diversification by including uncorrelated assets in one portfolio (AsafoAdjei et al., 2022; Chakrabarti and Das, 2021). Systematic risk is affected by external factors such as the rise of interest rates and inflation (Phuoc et al., 2018). This risk is, therefore, more difficult for risk managers to control and has led to the global financial crisis (Vishaal et al., 2018).

In portfolio management, systematic risk is evaluated as beta through the Capital Asset Pricing Model (CAPM) theory (Abonongo et al., 2017). Developed by Sharpe (1964) and Lintner (1965), beta is defined as the covariance between asset returns and market returns in proportion to the market return variance (Chakrabarti and Das, 2021). There is a trade-off between return and risk, and high-risk investments have the potential to yield higher returns. Hence, assets with a beta greater than the market are seen as aggressive securities and have a high expected rate of return. In contrast, defensive securities have a lower beta value than the market and have lower returns. (Challa et al., 2018; Sarraj and Mabrouk, 2021). Beta aids investors in choosing the portfolio of assets to invest in; high tolerant risk investors will invest in aggressive stocks, and risk averse investors will invest in defensive stocks.

2.1.1 Importance of risk management.

Risk in the financial market causes dire consequences for investors and the economy, as seen by the past financial crisis. Risk management is a form of anticipation of risk and birthing better strategies to avoid its impact on investments. Regulations such as the Basel Accords for financial institutions were constructed to deal with credit risk, operational risk, and market risk by having enough capital to cushion the default (Herring, 2004). The government has also developed depository insurance schemes to provide cash to keep defaulting intuitions operational during a financial crisis (Demirguc-Kunt et al., 2015). Statistical models and advanced computerized algorithms such as machine learning have been evolved to forecast and evaluate this risk (Nasteski, 2017). These statistical models have been discussed below.

2.1.2 Theory of Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are machine learning algorithms used to simulate the human learning process (Nasteski, 2017). They consist of a web of artificial neurons that work together to simulate the structure and functions of biological neurons (Krenker et al., 2011). The group of biological neurons forms a central nervous system; it can take in information from the environment, process it, interpret it, and respond appropriately to the inputted information. The architecture of the ANNs consists of the input layer, hidden layer, and output layer analogous to the central nervous system consisting of the dendrite, Sona, and axon (Gurney, 1997; Qiu and Song, 2016). The input layer (“dendrite”) takes in input variables from time series data, the hidden layer (“Sona”) decodes the nonlinear characteristics of the information, and finally, the output layer ("axon") generates the necessary output (Qiu and Song, 2016). The number and/or arrangement of these layers is related to the type of problem the network is solving. For example, the number of hidden layers can be more than one, but traditionally, one layer is enough (Yan and Ouyang, 2017).

2.1.3 Structures of Artificial Neural Networks

The hidden layer is part of the three-part segmentation of the ANN described above. In them, information can either be transmitted in a forward linear fashion or also be looped backward. The architecture of ANNs includes feedforward and feedback architecture. In a feedforward network, information moves in one direction but can move in opposite directions in the feedback structure (Krenker et al., 2011). In 1990 Elman introduced the Elman recurrent neural network (ERNN), which is part of the feedback topologies; these recurrent neural networks consist of four layers the input layer, content units, the hidden layer, and the output layer (Wang et al., 2018). The output of the hidden layer has the same number of neurons as the recurrent neurons feedback into the context layer at a constant weight value of one (Wang et al., 2018).

The feedback loops allow for a time delay that increases the storage of information; this allows for studying the data patterns for accurate forecasting (Kumar Chandar, 2020; Wang et al., 2016; Yan and Ouyang, 2017). This property is also advantageous for sequence/stack problem processing; however, the ERNN has a vanishing gradient problem, which leads to inaccurate prediction of weights and biases (Kumar Chandar, 2020; Samarawickrama and Fernado, 2017). The ERNNs are reliant on recent memory to forecast, and therefore, the network cannot predict patterns of time series data from the distant past (Kumar Chandar, 2020).

The different neural network topologies are advancements of the previously developed network: for example, the Long Short-Term Memory (LSTM) was developed to overcome the limitations of ERNN. LSTM is more advanced than most recurrent neural networks because it can predict correlated events no matter how long the lag between them is (Krenker et al., 2011). LSTM consists of memory modules and gates such as the forget gate, input gate, and output gate (Samarawickrama and Fernado, 2017). The function of the forget gate is paired with a sigmoid activation function responsible for the fate of the information variable on whether it is stored or deleted. The external input gate is also paired with the sigmoid activation function to update the information, and finally, the output gate controls the flow of output information (Yan and Ouyang, 2017). These memory conservations make them even more reliable for forecasting.

2.1.4 Learning methods in Artificial Neural Networks

To function accurately, the ANN model must learn the properties and patterns of the data about to be forecasted. The different architectural networks deploy different learning algorithms; these include supervised learning, semi-supervised learning, unsupervised learning, and more. These techniques aim to study the trends of financial time series data and formulate the mathematical models that best describe the classes of data. Supervised learning consists of using labelled data to compute classification and regression problems (Nasteski, 2017). The classification problems are solved by segregating data into predefined classes, and regression generates a continuous value result (Krenker et al., 2011; Nasteski, 2017). Supervised learning requires human intervention in training stages to define sets of data and a more accurate forecasting relative to other learning methods (Nasteski, 2017). Unsupervised learning involves identifying clusters with similar properties of data without no human intervention (Krenker et al., 2011; Nasteski, 2017).

A more detailed view of supervised learning is demonstrated using Support Vector Machines (SVM). SVM is one example of a supervised learning classifier. SVMs were developed by Vapnik (1998) and use a structural risk minimization strategy useful for solving overfitting problems in machine learning (Chen and Hao, 2017). Overfitting problems occur when the model corresponds more to the training data and then fails to capture trends of other data inputted in the model. SVMs are also useful in the prediction of small samples of nonlinear data and stock pattern recognition (Yang et al., 2020). SVM finds the optimum separation point between linear separable data points; it is a hyperplane in a 2-dimensional space (Kewat et al., 2017). However, financial time series data is often nonlinear, and simply categorizing it by a simple linear plane is insufficient. To circumvent this, SVM then employs the Kernel trick, which maps the input variables into a new high dimensional feature space where data points can be separated (Kewat et al., 2017; Yang et al., 2020). This mining technique requires a lot of continuous training time, which is not useful in time sensitive financial markets (Cervantes et al., 2020; Su, 2021).

More classifiers, such as the k-Nearest Neighbors (KNN), have been developed. Data is grouped into clusters of different characteristics then ‘K’ odd data points of these clusters are selected and are closer to an unknown data point (Taunk et al., 2019). The unknown data point is classified by picking the closest subset of data points that are closest to the unknown data point and have similar properties (Singh et al., 2017). One of KNNs biggest advantage is the ability to extract useful quality data that can be used to produce accurate results from a heap of big data (Triguero et al., 2019). Random forests are another mining technique consisting of multiple decision trees (Zhu et al., 2019). It is efficient in predicting default probabilities than the above the mention techniques, it is fast however SVM is a better classifier and is does not experience the overfitting problems (Teles et al., 2021).

2.1.5 Empirical Evidence

Investors are strategic and take advantage of the market conditions to maximize profits. Therefore, they take long and short positions in the market, deciding whether to sell or buy security instruments (Qiu and Song, 2016). Investors rely heavily on forecasting models to inform their decision. The predicting ability of ANN models has been investigated heavily in the stock market. The stock market fluctuations are affected by political, economic, and trader expectations (Hu et al., 2018). The architecture of the ANN model allows it to extract patterns of unstructured, non-stationary, and complex nonlinear stock data. Hence, investors in the stock market are investigating the ANN model that can produce the best results.

Shastri et al. (2018) investigated the use of ANN and Sentiment analysis to forecast short term stock prices of apple stock. Hybrid models increase forecasting accuracy, and sentiment analysis is used to collect data in the news headlines that can influence stock price movements. The weakness of this model is choosing the right words in the news headlines that are in conjunction with stock fluctuations. Hu et al. (2018) also used a similar method to predict the direction of stock prices, using Google trends of the S&P 500 and Dow Jones Industrial Average index. Prastro et al. (2022) investigated the stock prices in emerging markets such as the Nairobi stock exchange over a period of five years, including the time of financial crisis, which is believed to have caused distortions in the results.

The efficiency of ANNs has been investigated in developed markets as well by predicting bank failures in the US (Le and Viviani, 2018). During the financial crisis, many banks experienced failure such as investment banks that were known to be pure play investment banks but were universal banks and used too much leverage, which saw the failure of these banks. Depository insurance in most countries bailed out banks, providing a safety net and improving regulation to prevent bank run-offs (Demirgüç-Kunt et al., 2015). Le and Viviani (2018) Predicted the failure of banks using traditional statistical models, ANNs, and other machine learning techniques. Banking ratios indicating profitability, liquidity, and operation efficiency were analyzed to forecast this banking failure accurately. Wanke et al. (2016) also investigated the operating efficiency of Malaysian Islamic banks using these neural networks, which were accurately predicted when a hybrid of TOPSIS accompanied the model.

In recent times, there has been an upward increase in the foreign exchange rate market, and it has become the world's biggest currency exchange (Islam et al., 2020). The currency exchange is important in estimating currency risk and allows policy planners to implement accurate fiscal policies (Lahmiri, 2017). Lahmiri (2017) modelled and forecasted the volatility of exchange rates using GARCH, ANN, and a hybrid of these models. The GARCH model is important in capturing characteristics of the data that include volatility clustering, which is the tendency of high volatility events to cluster together, rare volatility jumps, and leverage effect, which is seen by big price drops having a larger impact on volatility than an equally large price increase (Schmidt, 2019).

However, the GARCH models and their optimized models assume that the data is linear and stationary, which is often not the case (Lahmiri, 2017). Hence, feeding GARCH results to the ANN does not produce highly accurate results. The distinction of Lahmiri's (2017) work is that technical indicators are used as input to the ANN; these use historical data patterns to predict an asset's future price. The historical patterns of asset market information will repeat themselves in the future. Islam et al. (2020) accessed the latest research in FOREX currency prediction and found that machine learning techniques were the most explored in forecasting the volatility of this market. Neural networks, optimization techniques, and pattern-based approaches were the most investigated methods.

In emerging markets, it is often hard to forecast the price direction of certain securities/commodities due to a lack of infrastructure, which leads to a lack of information about securities. South African market has the Johannesburg Stock Exchange, which provides some information about companies and markets, allowing for forecasts to be done. Ayankoya et al. (2016) investigated the estimation of maize price at the end of the trading day using these neural networks. Isenahd and Olusanyu (2015) also investigated ANN models in the Nigerian stock exchange, which were found to be inefficient. This inefficiency is often accompanied by insider trading, and hence, taking advantage of the market to make profits is not done in a "fair play" system like developed markets.

Moreover, the machine learning techniques were compared with traditional statistical methods in this research and the machine learning techniques were able to forecast 45% compared to the 27% ARIMA forecasts of the log returns in this Nigerian market. Prastro et al. (2022) investigated stock prices using the Nairobi stock exchange over a period of 5 years from 2008-2012. Initially, the forecasted stock price was accurate and closely followed the trend of the actual data. However, the ANN forecast started having a large difference, and it is argued that the small difference in closing price data is the reason for this inadequacy (Prastro et al., 2022). However, it can also be caused by the high volatility in the data due to the financial crisis that had recently occurred due to the time when the research was carried out, and a better training technique than the backpropagation can be utilized. It is thought that this learning method suffers from slow learning speed (Bou-Hamad and Jamali, 2020)

2.1.6 Traditional statistical models in Risk estimation.

Risk estimation for players in the market is important for investments and policy making. Researchers have developed statistical tools over time to ease the prediction of risk. The earliest form of forecasting involves pattern recognition and using this behavioral trend to check the probability of events reoccurring. ARIMA models are the earliest statistical form of "Letting the past predict the future," using a univariate linear regression with lagged variables and error terms (Ekinci, 2021). This model is popular, easy to use, and highly accurate in predicting short term forecasts such as daily stock prices (Wahyudi, 2017). Strategic investors want to maximize profits and consider a wide range of uncorrelated stocks to include in their portfolios. Hence, Challa et al. (2018) predicted the beta values of stocks in the Bombay Stock Exchange (BSE). Ten stocks were Aggressive stocks, twelve were comparable to the market index, and eight were defensive stocks (Challa et al., 2018).

In theoretical terms, it would have been estimated that more companies were going to be riskier than the market index because the Indian market is developing. Therefore, the empirical result supports the theory since many factors can lead to more volatile stocks. Moreover, Anon and Singh (2019) also investigated volatility forecasting in India using ARIMA models, but with different risk measures compared to the beta estimation. The Parkinson method (which measures high and low daily prices) is found to be the better volatility estimator accompanying the Arima models (Anon and Singh, 2019). The National Stock Exchange, which also encompasses the BSE companies, was used to advance the accuracy of prediction by giving lower MSE and MAD values. Arima models alone are still very limited in estimating accurate long horizon forecasts and are mostly used because of their simplicity, structure, and acceptable estimation performance (Wang et al., 2018).

In addition, Dinh (2020) used ARIMA models to forecast credit risk in China and Vietnam; the results reflected the different policies applied by the central banks of these two countries to control the GDP to credit risk ratio. Credit/leverage is important as it is the cheapest source of funding, and firms involved in the production of goods and services use it in the capital structure and hence are exposed to credit risk, warranting the significance of its estimation (Smith, 1986). ARIMA models are not only used in the financial space but have been in other sectors as well. In the dawn of COVID-19, governments were concerned about identifying high risk areas; to implement policies to deal with the virus. Arora et al. (2021) used five-month COVID-19 data to forecast highly infectious areas. It is worth noting that the ARIMA models analyze the linear characteristics of time series data.

Sharpe (1964) introduced the CAPM, and it generates the return on an asset with a linear relationship to the systematic risk (beta). Due to the stock exchange being in their infancy stages in the African markets, Alagidebe et al. (2017) investigated the validity of the CAPM in the South African market. The CAPM was found to be an efficient estimator of risk ex ante the financial crisis and less efficient ex post the crisis. Ghanian stock exchange was also found to have three defensive stocks and four stocks that are like the market index using the CAPM (Abonongo et al., 2017). The expectation from this research is that the Ghanian stock would have more aggressive stocks due to macroeconomic shocks that emerging markets are facing.

In addition, CAPM was developed by Markowitz in the 1950's and had originally thought it was only useful in portfolio selection (Sarraj and Mabrouk, 2021). However, it has been useful as an index in interpreting market fluctuations. It is now mostly known for the estimation of a required rate of return for a level of risk called the beta coefficient (Abonongo et al., 2017). Through the modern portfolio theory, Sharpe and Lintner extended the theory and certain assumptions, such as asset markets being frictionless, information being free, demonstrating an efficient market, and that investors can borrow and lend unlimitedly at a risk-free rate (Tlemsani et al., 2020). These assumptions pose a question on the validity of the CAPM since they do not hold up most of the time. Tlemsani et al. (2020) made a case in investigating the validity of the CAPM that the investors cannot borrow at the risk-free rate due to the USA (United States of America) treasury bills (risk-free asset) not being stable for the past five years.

The failure of the CAPM may also be due to unsuitable methods for measuring the parameters of the CAPM equation. Incorrect measurements of beta can lead to failure of the CAPM; for example, beta calculated from monthly returns contains larger errors and standard deviations than beta calculated from daily returns (Chen et al., 2022). The CAPM also has limitations when dealing with time series data. Time series data is collected over time and, most times, is nonstationary. As a result, the data used in the CAPM will contain certain characteristics such as seasonality, cycles, and upward trends (Sarraj and Mabrouk, 2021). This means it is exceedingly difficult to describe the properties of these data. Other researchers, such as Sharpe, Lintner, and Brennan, have since extended the CAPM to include transaction costs and taxes when using CAPM to evaluate stock selection (Sarraj and Mabrouk, 2021).

Despite their utility, ARIMA models are also only effective in short-term forecasting and are only able to deal with linear characteristics from data and not nonlinear characteristics of data (Wahyudi, 2017). Recently, there has been a development of technology in financial markets that led to these markets being highly correlated. Therefore, the data from these markets is highly complex and requires sophisticated models. The data generated is of high volume, variety, and velocity and is termed big data; these data are the basis for informed decision-making in financial institutions (Alexander et al., 2017). Managers' ability to make informed decisions is now based on the lack of efficient models rather than the availability of data (Alexander et al., 2017). Hence, different advanced models that consider all linear and nonlinear aspects of the data must be used to increase forecasting accuracy.

Hybrid models, such as the ARIMA model and machine learning techniques, are proposed to overcome the problems facing traditional statistical models. Any hybrid models aim to compensate for each other's weaknesses and produce better predictive models. Su (2021) investigated a hybrid of ARIMA models and a Support Vector Regression (SVR) model and found out this hybrid was not only more accurate in forecasting but was also a stable error curve. Engle (1982) and Bollerslov (1986) extended the ARIMA model by proposing the ARCH and GARCH. These considered that the variance is not constant but is said to be fluctuating. In comparison to ARIMA models, ARCH and GARCH are better estimators of time series data as their mean variance fluctuates from time to time.

However, the ARCH and GARCH models are accurate in capturing only the symmetrical properties of the data (Dwarika et al., 2021). Extended GARCH models such as EGARCH, TGARCH, and APARCH were introduced to capture the asymmetric characteristics such as leverage effect and volatility clustering. In the literature, it seems EGARCH is most efficient at capturing these properties, although in some instances they do not capture them. Schmidt (2019) investigated the accuracy of the extended GARCH models under the COVID-19 crisis. This shock to the market caused high volatility of returns, hence better models were ought to be employed in forecasting. The GJR and EGARCH were found to be better predictors of Nordic indices in this market (Schmidt, 2019).

Furthermore, there are external variables that influence the asset returns in the market. Kristjanpoller and Michell (2018) proposed the use of Markov Switching to determine the most valuable variable that influences the movements in the returns. This, accompanied by machine learning techniques, increased risk forecasting. In emerging markets, stock exchanges are new, and regulators are still dealing with an unstable developing market. The emerging markets are characterized by illiquidity in the market, frequent internal and external shocks, and a higher level of insider trading (Smolović et al., 2017).

The Shanghai Stock Exchange EGARCH outperforms TARCH models (Lin, 2018). Moreover, in the South African market, the EGARCH also outperform APARCH and GJR, even though the asymmetric properties were not fully captured (Dwarika et al., 2021). In emerging markets, there is a tendency for symmetrical effects, and as a result, GARCH models outperformed the extended asymmetrical model in the Malaysian market (Bahtiar, 2020).

2.1.7 Machine Learning vs Statistical Methods

This paper aims to forecast time series data using Artificial Neural Networks. The efficiency of ANNs has been investigated in developed markets by predicting bank failures in the US (Le and Viviani, 2018). The machine learning techniques were compared with traditional statistical methods. The machine learning techniques were able to extract and forecast the complex data used and this is due to having the sigmoid function built into them. Hamid and Iqbal (2004) also argue that the potential of neural networks to forecast accurately is more of an art than science around the training methods and topologies used. Artificial neural networks also have a wide applicability to forecast any time series data in various fields. Abraham et al. (2020) compared the effectiveness of ANNs against the Classical Method of time series analysis; it shows that ANNs outperform classical methods even though classical methods still produce good models.

These machine learning techniques have been proven to outperform most models used in forecasting. With the developments in big data analysis, financial institutions are out to employ these techniques to analyze data. Data is the basis for proper decision making. As a result, there has been an integration of financial institutions and technology forming Fintech (Alexander et al., 2017). These offer financial institutions advantages such as cuts in costs, enhancement in security, and access to a broader range of the market (Al-Ajlouni and AlHakim, 2018). Bou-Hamad and Jamali (2020) made a novel discovery that by using ANN and cumulative returns with high persistence, one can accurately estimate long-horizon forecasts. This implies that portfolio managers can make one year beta forecasts and strategies for hedging risk and allocating assets in a portfolio. The research uses this novel discovery in estimating systematic risk.

3 Research Methodology and data

3.1 Methodology

The methodology is based on the research by Bou-Hamad and Jamali (2020) that for highly persistent time series data, data mining techniques such as ANNs outperform AR (1)-GARCH (1,1) in long-horizon (one-year) forecasts. This novel discovery is used to estimate beta values for the years 2018-2019 and the year 2020-2021. To investigate the accuracy of the model in predicting beta during normal times and during a crisis such as COVID-19 that introduced a shock to the market. The closing stock price data is obtained for both emerging and developed markets. Annualized returns are calculated from the stock prices because they are easier to work with and have attractive properties such as stationarity. The returns are also annualized because they exhibit a high persistence close to 1 that is in an autoregressive regression. The current value is highly explained by the lagged explanatory value.

$$r_t = 100 * Ln(\frac{p_t}{p_{t-1}}) \qquad [1]$$

Where rt *is* the yearly return, p_t and $p_{t-1}$are the closing price of the stock at the current year and previous year respectively.

The capital asset pricing model estimates securities return as a function of the market return. The asset return is the sum of the risk-free rate and the risk premium. The risk-free rate is the riskless asset, and the risk premium is the compensation an investor must receive for taking the risk on a risky asset. This risk that the investor bears is systematic (beta (β)). Each company's beta values are computed as the covariance between securities return and the market return in proportion to the market return variances, as seen below.

$$\beta_t = \frac{Covariance(r_i, r_m)}{Variance\ (r_i)} \qquad [2]$$

Where ri and rm are the firm's return and the market return, respectively.

The artificial neural network topology used consists of three layers: the input layer, the hidden layer, and the output layer. Before the model can be used in forecasting, training of the model is done. The data set from 2010-2017 will be used to train the model in this research. The training and testing data set is based on a ratio of 80:20; that is, 80% of data is used in training and 20% in testing. The multi-variable data is loaded into the input layer, and each variable is assigned a weight as in equation 3. The weights determine the importance and relationship of the input-variable in producing the output result y.

$$y(t) = \alpha_i + \sum_{i=0}^{p} w_{it} \cdot \beta_i \qquad [3]$$

where αj and $w$it are the bias and initial weights, respectively, and used in the input layer adjusted with the learning process, and βi is the beta value of a particular company.

The output $y(t)$ of the input layer is then passed to the hidden layer, where the activation function is applied to this value. The algorithm used in estimating and updating the weights is the Broyden-FletcherGoldfarb-Shanno algorithm. The logistic function is the activation function in generating the output. The logistic function adds the non-linearity complexity to the model. It is important as it decides whether a neuron should be activated and gives the ANNs a decision-making ability. It also helps the network recognize the complex patterns of the data (Prakarsh and Sharma, 2021). It is vital in constricting the output to a certain range to avoid computational issues. This function is the smooth approximation of the binary function; the binary function has two outcomes: 0 and 1. Zero (0) means the threshold was not met, and 1 implies the threshold was met.

Binary function:

$$y = \begin{Bmatrix} 1\ if\ w_i x_i\ \geq\ threshold \\ \hline 0\ if\ w_i x_i <\ threshold \end{Bmatrix} \qquad [4]$$

logistic function:

$$g(s) = \frac{1}{1 + e^{-s}} \qquad [5]$$

The hidden layer output is fed into the output layer, where an output is produced. This output is compared to the actual true data, and an algorithm is used to readjust the weights for a better approximation of the output. When a better approximation has been obtained, the historical data can be used to forecast future values. Test data values are then loaded into the ANNs package in R to recognize the patterns in the data before it can be used to forecast.

The accuracy of this model is tested using statistical accuracy measures such as the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). These accuracy measures calculate how much the beta produced by the model differs from the actual beta. The smaller the difference, the more accurate the model is in forecasting. These accuracy measures are simple and concise as the risk (i.e., beta) of the stocks used in the research can be computed and compared in absolute terms to the one forecasted by the model. MAE is advantageous over RMSE as it is robust to outliers in the dataset.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{tf}(\beta_t - \overline{\beta}_t)^2}{T_F}} \quad [6]$$

$$MAE = \frac{1}{T_F}\sum |\beta_t - \overline{\beta_t}| \quad [7]$$

where βt and $\ddot{\beta} t$ are the actual and the forecasted beta values.

3.2 Data

The data used in this paper is from the South African Market, which represents the emerging market, and the American (USA) market is used as the developed market. The data set is collected from Bloomberg. The closing stock price data is used to obtain returns used in the beta calculation. The South African market data is listed on the Johannesburg Stock Exchange (JSE), and the American data is obtained from the New York Stock Exchange (NYSE). The NYSE is fully developed when compared to the JSE. As a result, only 161 companies' stock data was used for a fair comparison. The companies are mostly spread across similar industries in both markets. The data used is for 11 years, from January 2010 to December 2021. Beta is forecasted for 2018-2019 and 2020-2021 to capture the difference and between forecast values before and after the COVID-19 shock in the market.

This specific collection data period is chosen because, in 2010, the financial market data set is assumed to have recovered from the disruptions of the 2008 financial crisis. Hence, the 2010-2018 data set is assumed to be the stable set for both emerging and advanced markets. The 2019-2021 data set is unstable due to the effect of the coronavirus on financial assets.

The list of companies whose beta forecasts are to be done for both markets is shown in the appendix. The data contains the symbol, company name, and the sector to which it belongs. Figures 1 and 2 represent the distribution of sectors to which the companies in this market belong. The South African market is dominated by the manufacturing, technology, and mining industries, as seen in the pie chart. The manufacturing and technology industries also dominate the American market. Most industries are similar making it easier to compare both markets.

The data will be used to forecast long-horizon systematic risk, divided into monthly, quarterly, and yearly. The accuracy of the forecast will be analyzed by how low the RMSE and MAE values are.

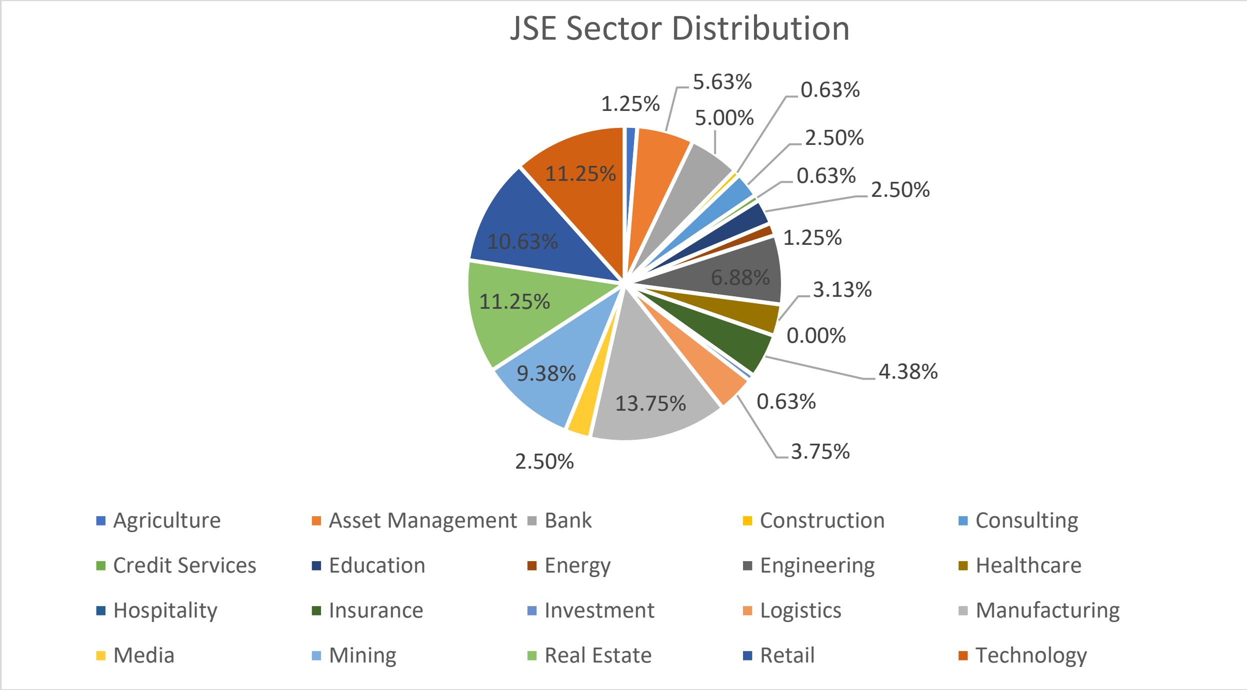

Figure 1: JSE Sector distribution

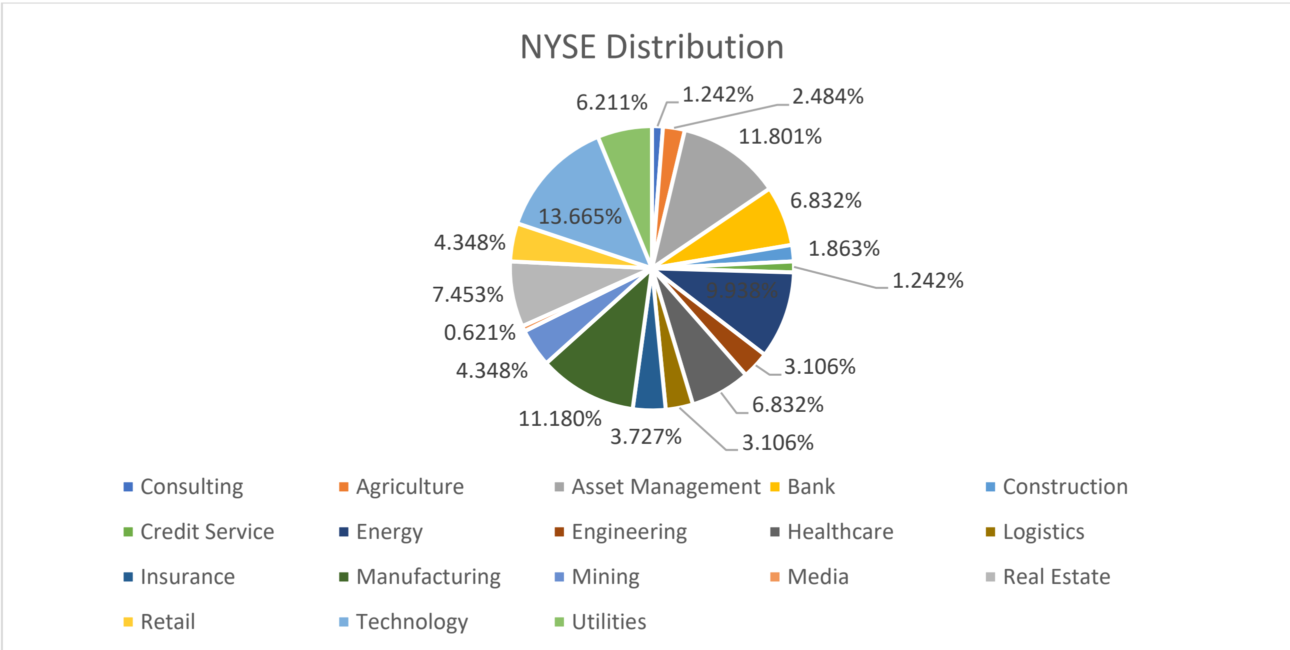

Figure 2: NYSE Sector Distribution

4. Results

4.1 Descriptive statistics.

4.1.1 Advanced Market Systematic risk Statistics:

The NYSE descriptive statistics of systematic risk (beta) from 2010-2021 are shown below. Attached to this paper is an excel file showing monthly descriptive statistics for both markets. The engineering, construction, credit service, and retail sectors have mean values above 1, above the market value of 1. Adding any company from these sectors to an investor's portfolio would raise the investor's risk; however, a higher return rate would be expected. Sectors such as logistics and healthcare have low mean beta values and are, therefore, defensive stocks. These kinds of stocks that do not flactuate rapidly with the market are good for risk averse investors.

Table 1: Descriptive statistics for the Yearly NYSE beta values

DESCRIPTIVE	AGRICULTURE	ASSET_MAN	BANKS	CONSTRUCT	CONSULTING	CREDIT_SERVICE	ENERGY
Mean	0.39	0.44	0.44	1.10	0.58	1.19	0.69
Median	0.82	0.45	0.09	0.58	0.44	0.42	0.88
Maximum	1.57	1.45	4.48	6.99	5.97	9.79	2.79
Minimum	-3.17	-0.75	-0.97	-1.95	-1.21	-1.55	-0.99
Std. Dev.	1.33	0.64	1.44	2.27	1.88	2.95	1.04
Skewness	-1.81	-0.34	1.93	1.48	2.02	2.21	0.10
Kurtosis	5.37	2.46	6.38	4.96	6.87	7.26	2.93
Jarque-Bera	9.34	0.38	13.12	6.30	15.67	18.86	0.02
Probability	0.01	0.83	0.00	0.04	0.00	0.00	0.99
Sum	4.63	5.26	5.31	13.20	6.90	14.33	8.31
Sum Sq. Dev.	19.49	4.54	22.74	56.89	39.00	95.77	11.90
Observations	12.00	12.00	12.00	12.00	12.00	12.00	12.00

DESCRIPTIVE	ENGINEERING	HEALTH_CARE	INSURANCE	LOGISTICS_	MANUFACT	MEDIA_AVE	MINING_AV
Mean	1.24	0.12	0.51	0.55	0.33	0.55	0.78
Median	0.65	0.32	0.65	0.21	0.67	0.32	0.51
Maximum	10.15	1.20	1.66	6.72	1.39	5.23	6.23
Minimum	-0.77	-2.10	-0.85	-4.33	-1.68	-1.45	-2.12
Std. Dev.	2.92	0.93	0.75	2.57	1.00	1.71	2.03
Skewness	2.61	-1.08	-0.61	0.69	-1.00	1.67	1.52
Kurtosis	8.67	3.66	2.69	4.68	2.62	5.94	5.69
Jarque-Bera	29.65	2.54	0.80	2.38	2.07	9.90	8.24
Probability	0.00	0.28	0.67	0.30	0.35	0.01	0.02
Sum	14.90	1.46	6.15	6.59	3.93	6.57	9.33
Sum Sq. Dev.	93.79	9.49	6.13	72.52	11.01	32.03	45.18
Observations	12.00	12.00	12.00	12	12	12	12

DESCRIPTIVE	REAL_ESTA	RETAIL_AV	TECHNOLO	UTILITIES_A
Mean	0.04	1.01	0.56	0.67
Median	0.40	0.82	0.57	0.77
Maximum	0.91	3.99	2.35	1.34
Minimum	-2.46	-1.41	-1.03	-0.60
Std. Dev.	1.00	1.40	0.85	0.51
Skewness	-1.42	0.38	0.14	-1.19
Kurtosis	4.25	3.14	3.46	4.43
Jarque-Bera	4.84	0.30	0.14	3.87
Probability	0.09	0.86	0.93	0.14
Sum	0.43	12.11	6.75	8.02
Sum Sq. Dev.	10.96	21.55	8.03	2.82
Observations	12	12	12	12

4.1.2 Emerging market Descriptive Statistics

The South African sectors shown below depict low systematic risk values, and negative values indicate that these sectors move in a direction opposite to the benchmark. For an investor, this is an unpredictable market that will not yield positive returns, even for a risk averse investor. The technological advancements in this market are not established enough for the financial market to reflect the real economy hence the low uncorrelation mean values.

Table 2: Descriptive statistics of the Yearly JSE beta values.

DESCRIPTIVE	AGRICULTURE	ASSET_MAN	BANKS_AVE	CONSTRUCT	CONSULTIN	CREDIT_SE	EDUCATION
Mean	0.006	-0.019	-0.009	-0.012	0.001	-0.115	-0.022
Median	0.005	-0.004	0.000	-0.012	0.002	-0.055	-0.001
Maximum	0.025	0.007	0.033	0.071	0.043	0.225	0.014
Minimum	-0.008	-0.170	-0.150	-0.111	-0.038	-1.146	-0.243
Std. Dev.	0.009	0.049	0.047	0.041	0.030	0.343	0.070
Skewness	0.434	-2.733	-2.522	-0.545	-0.008	-2.443	-2.905
Kurtosis	2.944	9.006	8.483	5.210	1.545	8.187	9.689
Jarque-Bera	0.379	32.979	27.750	3.037	1.058	25.388	39.249
Probability	0.827	0.000	0.000	0.219	0.589	0.000	0.000
Sum	0.071	-0.226	-0.110	-0.138	0.016	-1.376	-0.262
Sum Sq. Dev.	0.001	0.026	0.024	0.018	0.010	1.298	0.054
Observations	12	12	12	12	12	12	12

DESCRIPTIVE	ENERGY_A	ENGINEERI	HEALTHCAR	HOSPITALITY	INSURANCE	LOGISTICS_	MANUFACT
Mean	-0.005	-0.017	-0.017	-0.015	-0.016	-0.018	-0.006
Median	0.002	0.002	-0.003	-0.007	-0.008	-0.002	-0.002
Maximum	0.032	0.032	0.019	0.022	0.011	0.020	0.009
Minimum	-0.071	-0.216	-0.163	-0.135	-0.130	-0.221	-0.071
Std. Dev.	0.026	0.064	0.048	0.040	0.037	0.065	0.021
Skewness	-1.248	-2.790	-2.543	-2.53	-2.70	-2.88	-2.58
Kurtosis	4.775	9.316	8.399	8.49	9.01	9.63	8.52
Jarque-Bera	4.690	35.512	27.510	27.90	32.68	38.59	28.54
Probability	0.096	0.000	0.000	0.000	0.000	0.00	0.00
Sum	-0.062	-0.199	-0.202	-0.176	-0.189	-0.212	-0.075
Sum Sq. Dev.	0.007267	0.045386	0.025799	0.017	0.015	0.046	0.005
Observations	12	12	12	12	12	12	12

DESCRIPTIVE	MEDIA_AVE	MINING_AV	REAL_ESTA	RETAIL_AV	TECHNOLO
Mean	-0.014	-0.008	-0.022	-0.016	-0.006
Median	-0.002	0.005	-0.003	0.000	0.001
Maximum	0.069	0.060	0.022	0.010	0.021
Minimum	-0.232	-0.129	-0.271	-0.196	-0.075
Std. Dev.	0.074	0.045	0.079	0.057	0.025
Skewness	-2.31	-1.52	-2.93	-2.96	-1.88
Kurtosis	7.89	5.82	9.78	9.90	5.97
Jarque-Bera	22.58	8.61	40.08	41.35	11.46
Probability	0.00	0.01	0.00	0.00	0.003
Sum	-0.164	-0.10	-0.27	-0.19	-0.071
Sum Sq. Dev.	0.060	0.02	0.07	0.04	0.007
Observations	12	12	12	12	12

4.2 ANN model Architecture

The following figures demonstrate the general structure and an example of a structure used when forecasting in this paper. As previously mentioned in the methodology, the ANN model predicts data after training. Some input variables are used to train the model, allowing it to extract patterns and non-linear characteristics of the data set, allowing it to forecast accurately. The figures below demonstrate the monthly, quarterly, and yearly forecasting structure. In figure 4, the beta values of the years from 2010 to 2020 have been used to forecast the systematic risk of the year 2021. The middle (hidden) layer used in figure 4 is the (4,2) hidden layer, and the accuracy of the model relies on the kind of hidden layer used. The numbers shown in figure 4 are the weights that are used in forecasting the systematic risk as the information is transmitted from one layer to another. When these values satisfy the threshold, the activation function activates the neurons, which allows the data to be carried forward.

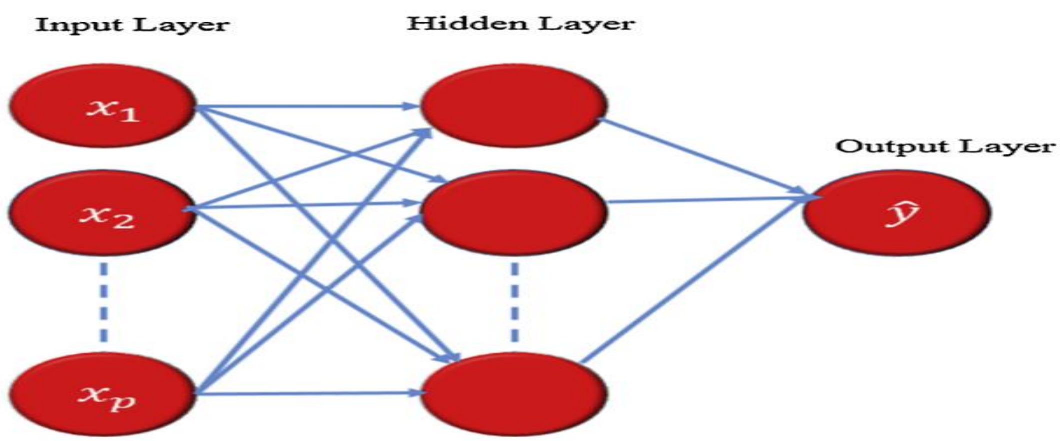

Figure 3: General ANN Architecture

Source: Bou-Hamad, I. and Jamali, I., 2020, *Architecture of an Artificial Neural Network.*

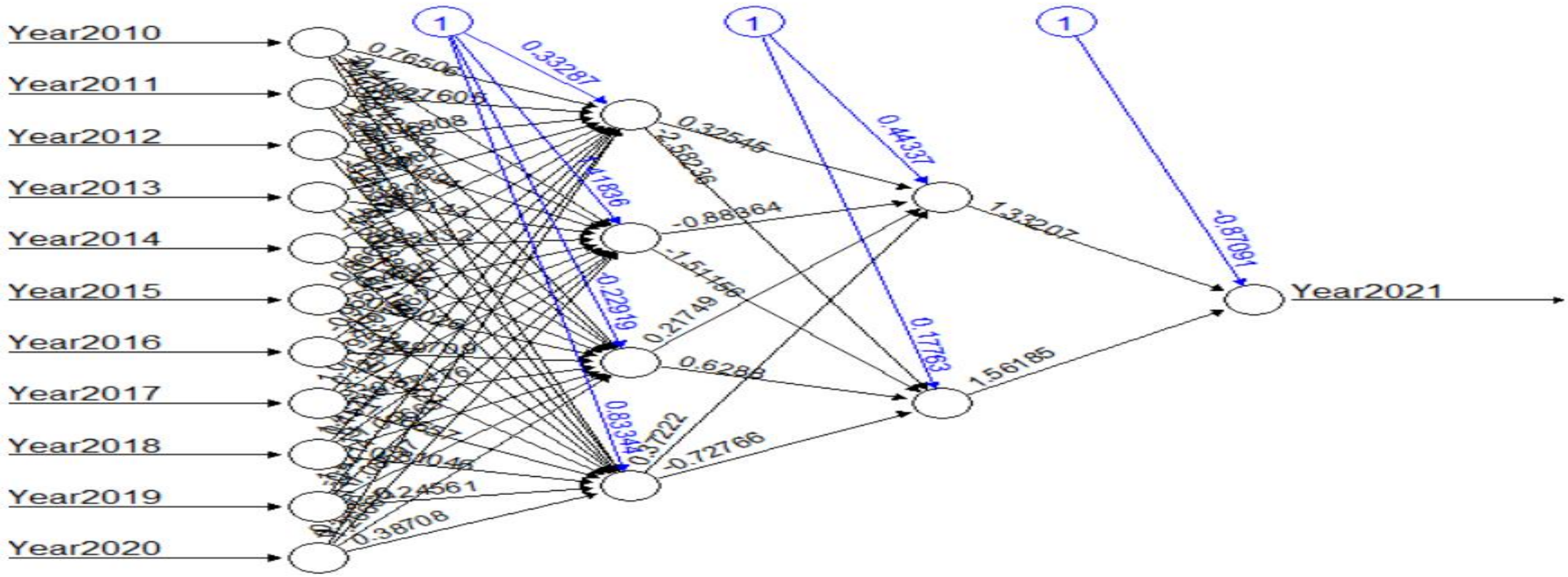

Figure 4: Computed ANN model Forecasting Year2021 Systematic risk

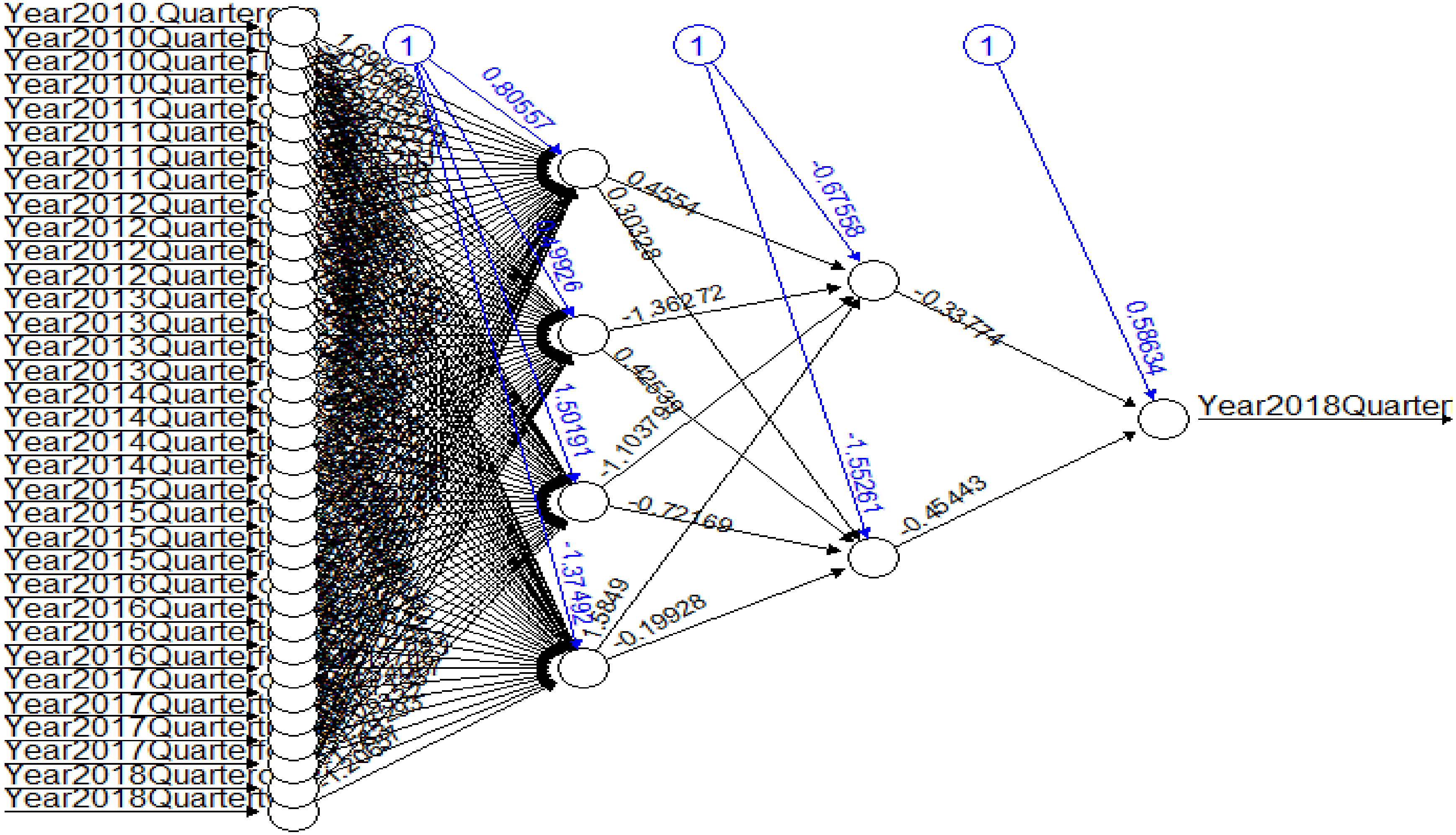

Figure 5: Computed ANN Model Forecasting Quarterly systematic risk for 2018.

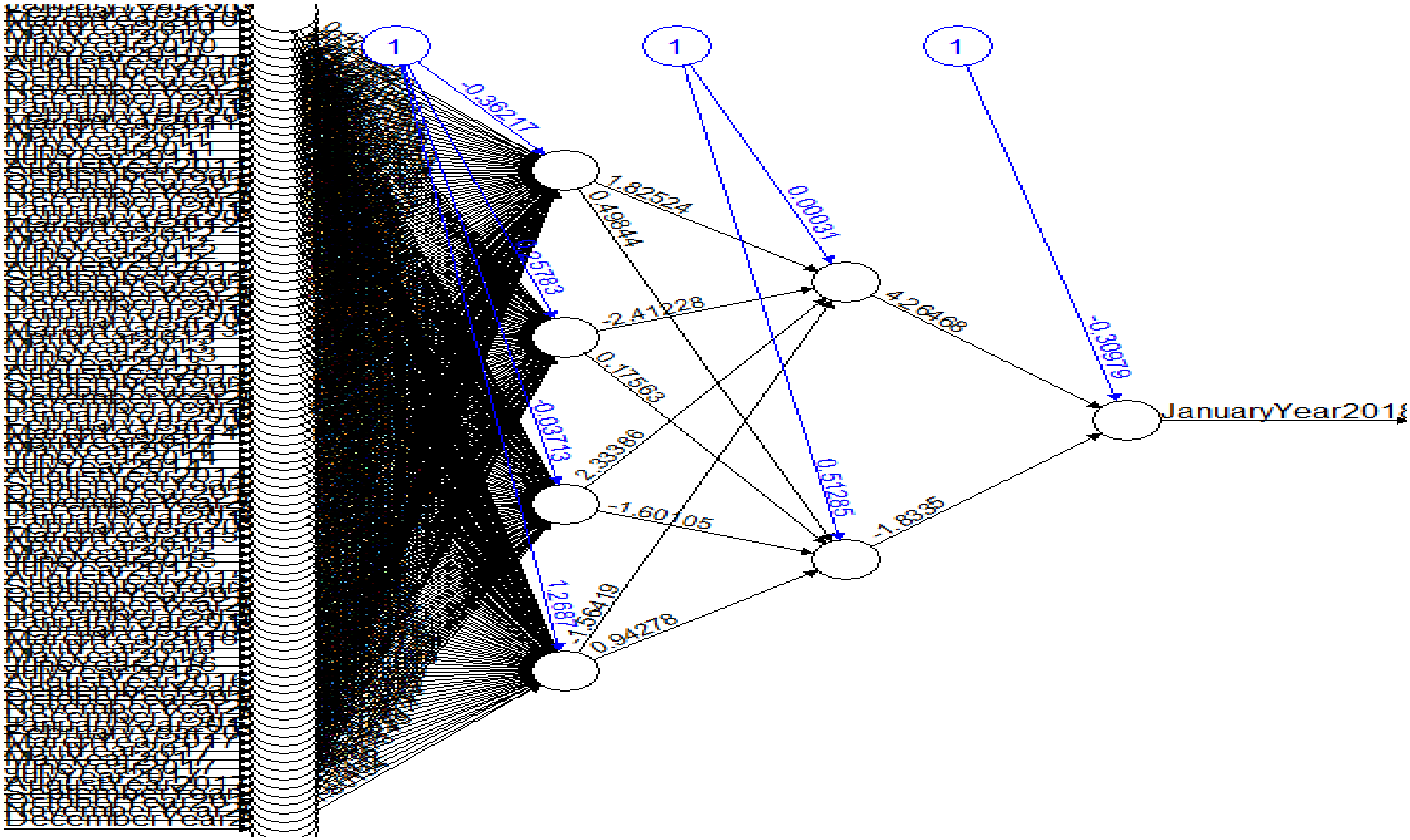

Figure 6: Computed ANN model forecasting Monthly Systematic risk for January 2018

4.3 Yearly Systematic Risk for different markets.

Attached to this research paper is an excel file demonstrating the actual and predicted yearly systematic risk for all the sectors in both markets. The accuracy of the model in predicting time series data is explained below as time horizons are increased from monthly, quarterly, and yearly. Consequently, the persistence of the data increases as the time horizon increases.

The accuracy of the ANN model is determined by estimating the RMSE and MAE values in the next section. However, as seen in table 3, the advanced markets contain a mixture of aggressive and defensive stocks. In the emerging market, however, most stocks are surprisingly defensive and have low beta values over time.

In the NYSE the construction, credit service, engineering, and retail sectors contain aggressive stocks relative to other sectors. The less risk averse investors can follow the stocks in these sectors to increase their returns.

Table 4 shows that only a few stocks in the South African market are aggressive, and most stocks are defensive. The global impact of the coronavirus crisis is shown across the sectors of the NYSE market, but the sectors of the JSE do not show any drastic changes in the size of beta. NYSE sectors report low values in 2020 relative to previous years.

4.4 Accuracy of the ANN model using RMSE AND MAE

Tables 3 and 4 below show the monthly RMSE and MAE values for the forecasted beta in emerging and advanced markets. The model produced smaller RMSE and MAE for the emerging market compared to the advanced market. However, both the RMSE and MAE average monthly values of the advanced market decreased from 2018 to 2020, and this supports the theory that ANN models are accurate in long-horizon prediction. However, the decreasing trend is not pronounced in both these markets across months in one year. For example, a constant decrease in 2018 from January to December has not been observed.

Table 3: Summary of the Monthly South African market forecasts.

	2018		2019		2020		2021	
Month	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
January	0.038	0.024	0.055	0.035	0.145	0.082	0.069	0.041
February	0.058	0.037	0.58	0.039	0.022	0.014	0.063	0.045
March	0.24	0.15	0.15	0.078	-0.125	0.056	0.30	0.18
April	0.016	0.010	0.035	0.022	0.025	0.014	0.19	0.088
May	0.11	0.062	0.53	0.014	0.064	0.026	0.049	0.034
June	0.018	0.013	0.39	0.113	0.048	0.037	0.20	0.11
July	0.12	0.052	0.028	0.018	0.047	0.033	0.039	0.026
August	0.047	0.034	0.069	0.032	0.426	0.19	0.090	0.048
September	0.042	0.021	0.013	0.009	0.038	0.025	0.29	0.070
October	0.023	0.014	0.16	0.097	0.051	0.035	0.16	0.060
November	0.037	0.031	0.040	0.020	0.053	0.034	0.42	0.11
December	0.070	0.030	0.032	0.023	0.022	0.015	0.37	0.085
average	0.068	0.040	0.13	0.052	0.089	0.047	0.19	0.075

Table 4: Summary of the Monthly American market's forecasts.

	2018		2019		2020		2021	
Month	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
January	2.32	1.69	1.30	2.63	0.65	0.48	0.44	0.31
February	1.13	0.77	0.99	0.65	0.27	0.18	0.25	0.18
March	0.37	0.28	6.04	4.32	0.09	0.07	27.30	19.43
April	4.11	2.38	2.88	1.84	1.16	0.80	1.51	1.14
May	1.55	1.05	1.04	0.79	0.23	0.16	0.37	0.26
June	1.87	1.24	0.25	0.18	1.67	1.06	2.66	1.85
July	0.46	0.33	1.14	0.71	0.28	0.20	0.21	0.15
August	1.30	0.88	0.45	0.31	0.63	0.45	0.39	0.30
September	5.98	3.14	1.50	0.96	0.28	0.21	1.07	0.73
October	3.50	2.63	1.25	0.87	0.40	0.31	0.41	0.30
November	0.68	0.48	0.99	0.69	0.44	0.32	0.16	0.11
December	0.49	0.36	0.19	0.13	0.22	0.16	0.62	0.40
average	1.98	1.27	1.50	1.17	0.53	0.37	2.95	2.10

4.5 Quarterly forecasts.

The average quarterly forecasts for both emerging and advanced markets do not show a constant decrease in error across time. However, both error measures show a constant decrease across yearly quarters in the emerging market case. The advanced market case shows mixed results that decrease in certain years across quarters and others increase across quarters. The emerging market still produces fewer values for both error measures.

Table 5: Quarterly emerging market forecasts.

	2018		2019		2020		2021	
Quarter	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Quarter one	0.088	0.056	0.064	0.034	0.058	0.035	0.121	0.073
Quarter two	0.038	0.024	0.293	0.068	0.017	0.013	0.094	0.056
Quarter three	0.027	0.020	0.017	0.012	0.141	0.070	0.091	0.033
Quarter four	0.024	0.012	0.060	0.039	0.022	0.016	0.139	0.046
average	0.044	0.028	0.109	0.038	0.060	0.034	0.111	0.052

Table 6: Quarterly advanced market forecasts.

	2018		2019		2020		2021	
Quarter	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Quarter 1	0.82	0.65	0.93	1.01	0.12	0.09	6.10	4.47
Quarter 2	1.53	4.98	0.79	0.59	0.77	0.58	1.44	1.05
Quarter 3	2.12	1.20	0.49	0.35	0.29	0.22	0.38	0.27
Quarter 4	1.38	1.04	0.72	0.52	0.17	0.12	0.38	0.21
Average	1.46	0.97	1.48	0.64	0.34	0.25	2.05	1.50

4.6 Yearly forecasts

The following tables show the yearly forecasts of risk in both emerging and advanced markets. The model was also more accurate in forecasting emerging market data. The ANN model produced less error in its prediction of yearly returns, but there was no constant decrease in MAE or RMSE as time increased.

Table 7: Emerging market yearly forecast.

Year	RMSE	MAE
2018	0.029	0.018
2019	0.074	0.023
2020	0.040	0.023
2021	0.060	0.032

Table 8: Advanced market yearly forecast.

Year	RMSE	MAE
2018	0.73	0.54
2019	1.29	0.94
2020	0.29	0.21
2021	2.63	1.87

5. Discussion

The novel discovery of Bou-Hamad and Jamali (2020) that long-horizon forecasts using ANN models produce better forecasts is tested. The empirical evidence found in this investigation yields mixed results. The positive end side of the research is that the error measures in both advanced and emerging markets are low across time. Therefore, the ANN model has a high accuracy in forecasting time series data. These results are useful for financial institutions and portfolio managers who aim to estimate systematic risk ahead of time. The integration of technology into operations and systems of financial institutions allow for more accurate informed forecasts to be made and allows managers to reduce costs when managing portfolios. In addition, emerging market data is not as “clean” as advanced market data because the analysis of advanced market data shows that it reflects the economic environment better. Despite this, the ANN model is more accurate in forecasting this complex emerging market data than well-structured data; this is advantageous and provides an opportunity for ANN models to be investigated further. Moreover, the model forecasting ability is not impacted by shocks introduced to the market and influences the financial time series data (stock prices).

However, as seen in the above section, the error measures do not get lower as the time horizon of the forecast is increased. The yearly forecast error should be significantly lower than the monthly and quarterly error measures. This is observed in both markets. This does not support the novel discovery of Bou-Hamad and Jamali(2020), that as long-horizon is increased, the model accuracy increases. It is thought that since the research was conducted by forecasting the data of each market on a monthly, quarterly, and yearly basis, respectively. the model suffered from overfitting. This occurs when the models respond more to the training data than the inputted (test data) used for forecasting. This is possible because the underlying structure of the ANN model is that the model be fed with data for training to recognize patterns of the data over time.

6. Conclusion

The forecasting ability of the Artificial neural network model is investigated in this research. The ANN is tested in both South African and American markets, when the market is assumed to be stable (2018-2019) to when there is a global crisis, in this case, the coronavirus, which affected the stocks of many companies and post the crisis (2020-2021).

The ANN model uses neurons like biological neurons to study the patterns and behavior of data through time and be able to make accurate forecasts. The latest research shows that these machine learning techniques are more accurate in forecasting long-horizon time series data and outperformed ARIMA and random forests models. Therefore, this paper investigated this model's ability to forecast systematic risk to make well informed decisions when allocating assets in a portfolio. The empirical results demonstrate that ANN is accurate in forecasting systematic risk; the small RMSE and MAE error values demonstrate this.

However, the RMSE and MAE did not consistently get smaller as the time horizon was increased. This is a bit of a concern on the model's ability to forecast long-horizon time series data. It is, therefore, thought that the data used might have posed some problems for the model. The South African market data, for example, did not seem to reflect the real economy as there was no change in beta values when the coronavirus shock affected the market, and it also had extremely low beta values. The accuracy of the model can again be investigated by gathering more data on each section of the economy in the advanced market. The more the frequency of the data used in the model, the more accurate the model gets in forecasting.

ANNs accuracy in forecasting, however, adds to the incorporation of machine learning techniques in financial institutions that deal with large quantities of financial data. As a result, portfolio managers and investors will find the empirical results of this research interesting since the ANN is useful in predicting "unclean" complex data of the emerging market and producing better forecasts. This will help managers lower rebalancing costs.

However, despite their usefulness in forecasting time series data, these models still need to be investigated further as they were not able to support the theory put forth by Bou-Hamad and Jamali fully.

8. References

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9. Appendix

Table 9: South African Listed on JSE Used in Forecasting

Symbol	Name	Sector
ARL	Astral Food Limited	Agriculture
CKS	Crookes Brothers Limited	Agriculture
BAT	Brait PLC	Asset Management
CML	Coronation Fund Managers Limited	Asset Management
INP	Investec Group	Asset Management
LNF	London Fin Inv Group Plc	Asset Management
PPE	Purple Group Ltd	Asset Management
REM	Remgro ltd	Asset Management
SEP	Sephaku Holdings. Ltd	Asset Management
VUN	Vunani ltd	Asset Management
ZED	Zeder inv ltd	Asset Management
ABG	absa group limted	Bank
CPI	Capitec Bank Holding Limiteed	Bank
FSR	Firstrand Limited	Bank
NED	Nedbank Group Limited	Bank
RMH	RMH Holdings	Bank
RMI	Rand Merchant Inv Holdings ltd	Bank
SBK	Standard bak group ltd	Bank
SFN	Sasfin holdings ltd	Bank
RBX	Raubex group ltd	Construction
CGN	Cognition holdings ltd	Consulting
JSC	Jasco Electron HLDGS LTD	Consulting
MFL	Metrofile Holdings Ltd	Consulting'
PMV	Primeserv Group ltd	Consulting'
ADW	African Dawn Capital Ltd	Credit Service
ADH	ADvTECH Limited	Education
ADR	Adcorp Holdings Limited	Education
COH	Curro Holdings Limited	Education
WKF	Workforce Holdings	Education
EXX	Exxaro Resources Limited	Energy
OAO	Oando Plc	Energy
ACL	ArcelorMittal South Africa Ltd	Engineeering
BAW	Barloworld limited	Engineering
BEL	Bell Equipment Limited	Engineering
ETO	Etion Ltd	Engineering

HDC	Hudaco Industries Limited	Engineering
IVT	Invicta Holdings Limited	Engineering
MUR	Murray & Roberts Holdings	Engineering
RLO	Reunert ltd	Engineering
SSK	Stefanutti STCK holdings ltd	Engineering
WBO	Wilson Bayly Hlm-OVC ltd	Engineering
AEG	Aveng Limited	Engineering
ACT	Afrocentric Investment corporation	Healthcare
AIP	Adcock Ingram Holdings Limited	Healthcare
APN	Aspen Pharmacare Holding Limited	Healthcare
LHC	Life Healthcare Group Holding Limited	Healthcare
NTC	Netcare Limited	Healthcare
CLH	City Lodge Hotels	Hospitality
FBR	Famous Brands Limited	Hospitality
GPL	Grand Parade Investemnt Limited	Hospitality
SUI	Sun International Ltd	Hospitality
SUR	Spur Corporation ltd	Hospitality
CLI	Clientele Limited	Insurance
DSY	Discovery Limited	Insurance
FGL	Finbond Group ltd	Insurance
MTM	Momentum Metropolitan Holdings Limited	Insurance
SLM	Sanlam ltd	Insurance
SNT	Santam ltd	Insurance
TTO	Trustco Group holdings ltd	Insurance
BVT	The Bidvst Group Limited	Investments
GND	Grindrop Limited	Logistics
HCI	Hosken Consolidated Investments Limited	Logistics
OLG	OneLogix Group Ltd	Logistics
SNV	Santova Logistics ltd	Logistics
SPG	Super Group ltd	Logistics
TSG	Tsogo Sun Gaming ltd	Logistics
AHL	AH-Vest Ltd	Manufacturing
ANG	Anheuser-Busch InBev SA/NV	Manufacturing
ART	Argent Industrial Limited	Manufacturing
AVI	Avi limited	Manufacturing
BCF	Bowler Metcalf ltd	Manufacturing
BIK	Brikor ltd	Manufacturing
BRN	Brimstone Investement Corporation	Manufacturing
ENX	ENX Group Limited	Manufacturing
HLM	Hulamin Limited	Manufacturing
ISB	Insimbi IND HLDGS Ltd	Manufacturing

ITE	Italtile Limited	Manufacturing
KAP	KAP Industraial Holdings Limited	Manufacturing
MNP	Mondi plc	Manufacturing
MTA	Metair Investments Limited	Manufacturing
NPK	Nampak ltd	Manufacturing
OMN	Omnia holdings	Manufacturing
PPC	PPC Ltd	Manufacturing
SAP	Sappi Ltd	Manufacturing
SOH	South Ocea Holdings ltd	Manufacturing
SOL	Sasol Ltd	Manufacturing
TPC	Transpaco Ltd	Manufacturing
YRK	York Timber Holdings ltd	Manufacturing
AME	African Media ENT LTD	Media
CAT	Caxton and CTP Publisers and Printers Limited	Media
EMH	E Media Holdings	Media
EMN	E Media Holdings Ltd	Media
AFT	Afrimat Limited	Mining
AGL	Anglo American plc	Mining
ARI	African Rainbow Minierals Limited	Mining
DRD	DRDGOLD Limited	Mining
EPS	Eastern Platinum ltd	Mining
GML	Gemfields Group Ltd	Mining
HAR	Harmony Gold Mining Company limited	Mining
IMP	Imapala Platinum Holdings Limited	Mining
JBL	Jubilee Metals Group PLC	Mining
KIO	Kumba Iron Ore Limited	Mining
MCZ	MC Mining Ltd	Mining
MRF	Merafe Resource Limited	Mining
PAN	Pan African Resource Plc	Mining
RNG	Randgold & Expl Co ltd	Mining
WEZ	Wesiswe Platinum ltd	Mining
CCO	Capital & Counties Properties	Real Estate
EMI	Emira Property Fund Limited	Real Estate
FFA	Fotress REIT Limited	Real Estate
FFB	Fotress REIT Limited	Real Estate
GRT	GrowthpoinT Properties Limited	Real Estate
HYP	Hyprop Inv Ltd	Real Estate
MMP	Marshall Monteagle PLC	Real Estate
MSP	MAS P.L.C	Real Estate
NRP	Nepi Rockcastle N.V	Real Estate
OAS	Oasis Crescent Prop Fund	Real Estate

OCT	Octodec Invest ltd	Real Estate
PPR	Putprop ltd	Real Estate
RDF	Redefine Properties ltd	Real Estate
RES	Resilient REIT ltd	Real Estate
SAC	SA Corp Real Estate Ltd	Real Estate
TDH	Tradehold ltd	Real Estate
TMT	Tremation Capital Inv ltd	Real Estate
VKE	Vukile Property Fund Ltd	Real Estate
CLS	Clicks Group Limited	Retail
CMH	Combined Motor Holdings Limited	Retail
CSB	Cashbuild Limited	Retail
LEW	Lewis Group ltd	Retail
MRP	Mr Price Group Limited	Retail
NCS	Nictus ltd	Retail
OCE	Oceana Group Limited	Retail
PIK	Pick n Pay Stores LTD	Retail
RCL	RCL Foods ltd	Retail
RTN	Rex Trueforn Group	Retail
SHP	Shoprite Holdings ltd	Retail
SNH	Steinhoff int holdings Nv	Retail
SPP	The Spar Group ltd	Retail
TBS	Tiger Brands ltd	Retail
TFG	The Foschini group ltd	Retail
TRU	Trustworth	Retail
WHL	Woolworths holdings ltd	Retail
AEE	African Equity Emp Inv Ltd	Technology
AVV	Alviva Holdings Ltd	Technology
BLU	Blue Label Telecoms Limited	Technology
DTC	Datatec Limited	Technology
ELI	Ellies Holdings Ltd	Technology
EOH	EOH Holdings Limited	Technology
HUG	Huge Group Ltd	Technology
ISA	ISA Holdings ltd	Technology
LAB	Labat Africa Ltd	Technology
MIX	Mic Telematics ltd	Technology
MST	Mustek ltd	Technology
MTN	MTN Group Limited	Technology
NPN	Naspers Limited	Technology
NWL	Nu-World Holdings Ltd	Technology
PBG	PBT Group Ltd	Technology
TKG	Telkom SA SOC Ltd	Technology

TLM	Telemaster Holdings Ltd	Technology
VOD	Vodacom Group Ltd	Technology

Table 10: American Companies Listed on NYSE Used In Forecasting

Symbol	Name	Sector
CF	CF Industries Holdings, Inc.	Agriculture
ADM	Archer-Daniels-Midland Company	Agriculture
FDP	Fresh Del Monte Produce Inc.	Agriculture
FMC	FMC Corporation	Agriculture
ASA	ASA Gold and Precious Metals Limited	Asset management
BEN	Franklin Resources, Inc.	Asset management
BLK	BlackRock, Inc.	Asset management
BX	Blackstone Inc.	Asset management
MCI	Barings Corporate Investors	Asset management
MPV	Barings Participation Investors	Asset management
IGR	CBRE Global Real Estate Income Fund	Asset management
DNP	DNP Select Income Fund Inc.	Asset Management
DTF	DTF Tax-Free Income 2028 Term Fund Inc.	Asset Management
EOS	Eaton Vance Enhanced Equity Income Fund II	Asset Management
EQS	Equus Total Return, Inc.	Asset Management
EVV	Eaton Vannce Limited Duration Income Fund	Asset Management
FAM	First Trust/Abrdn Global Opportunity Income Fund	Asset Management
FCT	First Trust Senior Floating Rate Income Fund II	Asset Management
FEO	First Trust/Abrdn Emerging Opportunity Fund	Asset management
FFA	First Trust Enhanced Equity Income Fund	Asset Management
FMY	First Trust Mortgage Income Fund	Asset Management
GCV	The Gabelli Convertible and Icome Securities Fund Inc.	Asset Management
GDV	The Gabelli Dividend & Income Trust	Asset Management
BAC	Bank of America Corporation	Bank
BANC	Banc of California, Inc	Bank
TD	The Toronto-Dominion Bank	Bank
FBC	Flagstar Bancorp Inc	Bank
C	Citigroup Inc.	Banks
CS	Credit Suisse Group AG	Banks
DB	Deutsche Bank Aktiengesellschaft	Banks
FCF	First Commonwealth Financial Corporation	Banks
FHN	First Horizon Corporation	Banks
FNB	F.N.B Corporation	Banks
GS	The Goldman Sachs Group, Inc.	Banks
DHI	D.R. Horton, Inc.	Construction
DY	Dycom Industries, Inc	Construction

EME	EMCOR Group, Inc.	Construction
FCN	FTI Consulting, Inc.	Consulting
FDS	FactSet Research Systems Inc.	Consulting
BBDC	Barings BDC, Inc.	Credit Service
AGM	Federal Agricultural Mortgage Corporation	Credit Service
CVI	CVR Energy, Inc	Energy
DCP	DCP Midstream, LP	Energy
DHT	DHT Holdings, Inc.	Energy
DTE	DTE Energy Company	Energy
DUK	Duke Energy Corporation	Energy
SHEL	Shell plc.	Energy
DVN	Devon Energy Corporation	Energy
E	Eni S.p.A	Energy
EC	Ecopetrol S.A	Energy
ENB	Enbridge Inc.	Energy
EOG	EOG Resources, Inc.	Energy
EPD	Enterprise Products Partners L.P	Energy
EQNR	Equinor ASA	Energy
EQT	EQT Corporation	Energy
ESTE	Earthstone Energy, Inc.	Energy
FRO	Frontline plc	Energy
ABM	ABM Industries Incorporated	Engineering
ACM	AECOM	Engineering
AIR	AAR Corp.	Engineering
ARC	ARC Document Solutions, Inc	Engineering
CAE	CAE Inc.	Engineering
BDX	Becton, Dickinson and Company	Health
EHC	Encompass Health Corporation	Health
CI	The Cigna Group	Health care
AMN	AMN Healthcare Services, Inc	Health care
BAX	Baxter International Inc.	Healthcare
BHC	Bausch Health Companies Inc.	Healthcare
BIO	Bio-Rad Laboratories, Inc.	Healthcare
CVS	CVS Health Corporation	Healthcare
DHR	Danaher Corporation	Healthcare
DVA	DaVita Inc.	Healthcare
FMS	Fresenius Medical Care AG & Co. KGaA	Healthcare
AEG	American Financial Group	Insurance
AFL	Aflac Incorporated	Insurance
BRKS-A	Berkshire Hathaway Inc.	Insurance
BRK-B	Berkshire Hathaway Inc.	Insurance
CBZ	CBIZ, Inc.	Insurance
CNO	CNO Financial Group, Inc.	Insurance
CCL	Carnival Corporation & plc	Logistics
DAC	Danaos Corporation	Logistics

DS	Diana Shipping	Logistics
RCL	Royal Caribbean Cruises Ltd.	Logistics
FDX	FedEx Corporation	Logistics
ACCO	ACCO Brands Corporation	Manufacturing
AP	Ampco -Pittsburgh	Manufacturing
ATI	ATI Inc.	Manufacturing
B	Barnes Group Inc.	Manufacturing
BALL	Ball Corporation	Manufacturing
BGS	B&G Foods, Inc.	Manufacturing
BRFS	BRF S.A	Manufacturing
CAL	Caleres, Inc.	Manufacturing
CBT	Cabot Corporation	Manufacturing
CIR	CIRCOR International, Inc.	Manufacturing
KO	The Coca-Cola Company	Manufacturing
DAN	Dana Incorporated	Manufacturing
DAR	Darling Ingredients Inc.	Manufacturing
GD	General Dynamics Corporation	Manufacturing
ECL	Ecolab Inc.	Manufacturing
EMN	Eastman Chemical Company	Manufacturing
EPAC	Enepac Tool Group Corp.	Manufacturing
F	Ford Motor Company	Manufacturing
DIS	The Walt Disney Company	Media
GOLD	Barrick Gold Corporation	Mining
CNX	CNX Resources Corporation	Mining
COP	ConocoPhillips	Mining
CPE	Callon Petroleum Company	Mining
AEM	Agnico Eagle Mines Limited	Mining
FCX	Freeport-McMoRan Inc.	Mining
GFI	Gold Fields Limited	Mining
ACR	ACRES Commercial Realty Corp.	Real Estate
AKR	Acadia Realty Trust	Real Estate
ARR	ARMOUR Residential REIT, Inc	Real Estate
AXR	AMREP Corporation	Real Estate
CBRE	CBRE Group, Inc.	Real Estate
CCI	Crown Castle Inc.	Real Estate
CTO	CTO Realty Growth, Inc.	Real Estate
IRM	Iron Mountain Incorporated	Real Estate
EPR	ERP Properties	Real Estate
ESS	Essex Property	Real Estate
EXR	Extra Space Storage Inc.	Real Estate
FR	First Industrial Realty Trust, Inc.	Real Estate
ANF	Abercrombie & Fitch Co.	Retail
BBWI	Bath&Body Works, Inc.	Retail
BH	Biglari Holdings Inc.	Retail
BIG	Big Lots, Inc.	Retail

DPZ	Domino's Pizza, Inc.	Retail
AEO	American Eagle Outfitters, Inc.	Retail
EAT	Brinker International, Inc.	Retail
ABB	ABB Limited	Technology
T	AT&T Inc.	Technology
BB	BlackBerry Limited	Technology
BCE	BCE Inc.	Technology
BDC	Belden Inc.	Technology
BHE	Benchmark Electronics, Inc.	Technology
BMI	Badger Meter, Inc.	Technology
BR	Broadridge Financial Solutions, Inc.	Technology
CACI	CACI International Inc.	Technology
CAN	Canaan Inc.	Technology
CNMD	CONMED Corporation	Technology
CTS	CTS Corporation	Technology
DBD	Diebold Nixdorf, Incorporated	Technology
DD	DuPont de Nemours, Inc.	Technology
DHX	DHI Group, Inc.	Technology
DXC	DXC Technology Company	Technology
ESE	ESCO Technologies Inc.	Technology
FICO	Fair Isaac Corporation	Technology
TDS	Telephone and Data Systems, Inc.	T'echnology
AAPL	Apple Inc.	Technology
ACN	Accenture plc	Technology
ASGN	ASGN Incorporated	Technology
FERG	Fergson plc	Utilities
AES	The AES CORPORATION	Utilities
CMS-PB	Consumers Energy Company	Utilities
CMS	CMS Energy Corporation	Utilities
ED	Consolidated Edison, Inc.	Utilities
ETN	Eaton Corporation plc	Utilities
ETR	Entergy Corporation	Utilities
WTRG	Essential Utilities, Inc.	Utilities
FE	firstEnergy Corp.	Utilities
FTS	Fortis Inc.	Utilities