Banking, Money and International Finance

ARTIFICIAL INTELLIGENCE AND BIG DATA FOR FINANCIAL RISK MANAGEMENT

INTELLIGENT APPLICATIONS

Edited by

Noura Metawa, M. Kabir Hassan and Saad Metawa

ROUTLEDGE

Artificial Intelligence and Big Data for Financial Risk Management

This book presents a collection of high-quality contributions on the state-of-the-art in artificial intelligence and big data analysis as it relates to financial risk management applications. It brings together, in one place, the latest thinking on an emerging topic and includes principles, reviews, examples and research directions. The book presents numerous specific use-cases throughout, showing practical applications of the concepts discussed. It looks at technologies such as eye movement analysis, data mining or mobile apps and examines how these technologies are applied by financial institutions and how this affects both the institutions and the market.

This work introduces students and aspiring practitioners to the subject of risk management in a structured manner. It is primarily aimed at researchers and students in finance and intelligent big data applications, such as intelligent information systems, smart economics and finance applications and the internet of things in a marketing environment.

Noura Metawa is Assistant Professor of Finance at the College of Business Administration, University of Sharjah, Sharjah, UAE, and at the Faculty of Commerce, Mansoura University, Egypt.

M. Kabir Hassan is Professor of Finance in the Department of Economics and Finance at the University of New Orleans, Louisiana, USA.

Saad Metawa is Professor of Finance at the Faculty of Commerce, Mansoura University, Dakahliya, Egypt.

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Intelligent Applications

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Contributors

Hosny H. Abo Emira is a Teaching Assistant of Computer Science at Nahda University.

Prof. Mazin A. M. Al Janabi is a Full Research-Professor of Finance & Banking and Financial Engineering at Tecnologico de Monterrey, EGADE Business School, Mexico.

Nowshath K. Batcha is a Senior Lecturer at Asia Pacific University, Malaysia.

Zhenxing Bian is an Associate Professor at Software Engineering Department, Shandong Polytechnic College, Jining, Shandong, China.

Ahmed A. Elngar is an Assistant Professor at Faculty of Computers and Artificial Intelligence, Department of Computer Science, Beni Suef University, Beni-Suef City, Egypt.

Ge Guo is affiliated with the School of Management, Wuhan Donghu University, Wuhan, Hubei, China.

Tielin He is affiliated with the Harbin Finance University, Harbin, Heilongjiang, China.

Silvija Vlah Jerić is an Associate Professor at the Department of Mathematics at Graduate School of Economics & Business, Faculty of Economics & Business, Croatia.

Mohammed Kayed is Head of Computer Science Department, Faculty of Computer and Artificial Intelligence, Beni-Suef University, Beni-Suef City, Egypt.

Xinyan Li is affiliated with the School of Management, Wuhan Donghu University, Wuhan, Hubei, China.

Noura Metawa is Assistant Professor of Finance at the Faculty of Commerce, Mansoura University, Egypt, and at the College of Business Administration, University of Sharjah, Sharjah, UAE.

Saad Metawa is Professor of Finance at the Faculty of Commerce, Mansoura University, Dakahlia, Egypt.

Maha Metawea is Assistant Professor at Faculty of Business Administration, Delta University for Science and Technology, Egypt.

Santha Muniandy is a Finance Specialist at Baker Hughes, a GE company, Kuala Lumpur, Malaysia.

Weiqi Rao is affiliated with the School of Management, Wuhan Donghu University, Wuhan, Hubei, China.

Geetha A. Rubasundram is a Chartered Accountant at MIA and Chartered Management Accountant at CIMA. She is an Associate Member of the Chartered Institute of Management Accountants (CIMA) with a M.Sc in Auditing, Management Accounting & Information Systems from Skema Business School, France.

Aishath Shaiha Shareef is an Affiliate member for Association of Chartered Certified Accountants (ACCA). She is currently working as an Assistant Manager for Finance Department at State Electric Company, Maldives.

Tihana Škrinjarić, Ph.D., is an Advisory at the Croatian National Bank. Tihana was an Assistant Professor in the Department of Mathematics at the University of Zagreb, Zagreb, Croatia.

Yichen Song is affiliated with the Departments of Physics and Mathematical Sciences, University of Liverpool, Merseyside, Liverpool, United Kingdom.

Chengwei Zhang is affiliated with the School of Management, Wuhan Donghu University, Wuhan, Hubei, China.

19 **Yichen Song** Departments of Physics and Mathematical Sciences, University of Liverpool, Merseyside, Liverpool, United Kingdom

Author

Prof. Mazin A. M. Al Janabi is a full research-professor of finance & banking and financial engineering at Tecnologico de Monterrey, EGADE Business School, Mexico. He holds a PhD degree in nuclear engineering from the University of London, UK, and has more than 30 years of real-world experience in science and technology think tanks, engineering enterprises, financial markets and academic institutions and in many different roles. He has worked for top international financial groups (e.g., ING-Barings and BBVA) where he held senior management positions, such as Director of Global Market Risk Management, Head of Trading Risk Management and Head of Derivative Products. Prof. Al Janabi has strong interest for research and developments within emerging economies and has several publications in reputable refereed journals, books and chapters in books. His research and development in quantitative finance have been classified in the academic literature as *Al Janabi Model* for Liquidity Risk Management (Liquidity Adjusted Value-at-Risk, LVaR Model). Prof. Al Janabi has published in top-tiered journals, such as *European Journal of Operational Research*, *Journal of Forecasting*, *International Review of Financial Analysis*, *Physica A: Statistical Mechanics and Its Applications*, *European Actuarial Journal*, *Annals of Operations Research*, *International Journal of Finance & Economics*, *Applied Economics*, *Economic Modelling*, *Review of Financial Economics*, *Journal of Asset Management*, *Service Industries Journal*, *Journal of Modelling in Management*, *Studies in Economics and Finance*, *Emerging Markets Finance and Trade* and *Annals of Nuclear Energy*, among others.

1 Grey model as a tool in dynamic portfolio selection

Simple applications

Tihana Škrinjarić

1 Introduction

Stock price prediction today presents one of the main tasks investors need to do daily. It is not surprising that many quantitative methods and models have been developed to facilitate the prediction process, and still are being developed today. As Fabozzi et al. (2007) explain, quantitative finance today is developing at a rapid pace, due to the rising number of different investment possibilities, different markets, and computer capabilities. However, the process of predicting is a difficult and demanding task, due to the complex, volatile, highly noisy, dynamic, and chaotic nature of prices on stock markets (Tay and Cao, 2001; Klein and Datta, 2018; Kumar et al., 2020). All these characteristics represent problems in constructing an efficient prediction model (Khan et al., 2018). This has stimulated the research to develop many approaches within mathematical modelling, in general, in operations research, econometrics, and other areas, to facilitate the decision-making process based on the stock price prediction. One relatively newer area of the methodology is the grey systems theory (GST), in which many familiar approaches from operations research, differential equations applied in finance, and others are extended with the fact that data we all use in practice are "grey", i.e., it consists of uncertainties and the decision-maker does not have full information available (Liu et al., 2016). As many different problems in economics and finance contain incomplete information, data errors, and other inaccuracies, the grey methodology focuses on the approach where such issues are taken into consideration. This is especially true for the financial and stock markets, where a lot of information is generated daily and there exist data problems within big data.

Although many different approaches exist in terms of using mathematical and econometric models and methods as tools in stock price, return, and/or risk prediction, there are several reasons why the grey methodology

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could be used within this area of research and application. First of all, due to the explanation of the term "grey", it is understandable why it is useful to implement over financial data. Next, the methodology within GST is flexible in terms it can be applied in predicting time series, portfolio optimisation, coincidence analysis, constructing a ranking system in the decision-making process, etc. Thus, its versatility can be applied to different questions regarding portfolio selection over time. Some of the many different applications within other areas of research (not financial applications such as in this chapter) can be found in Škrinjarić (2021). However, the applications of GST models and methods are still not yet popular in many areas of the world, although the practicality of many of them. There exists research that employs the GST approach within the area of finance (please see the second section of this chapter), but there still exist some literature gaps.

That is why this chapter has the following contributions to the literature. Besides the usual part in which we show the results of the estimation part, the GST models are used as a basis in dynamic portfolio selection. Usually, the literature does not explain how to use such models in the decision-making process of when to invest or sell the portfolio or stock. A detailed analysis is provided in which we simulate trading based on the estimation results, and the simulated strategies are compared one to another based on several portfolio performance measures. Again, the literature usually either ignores the latter or does not compare the portfolio performance by using the measures which are relevant to investors. Finally, the estimation part is done by applying a rolling-window analysis in which the one-day out-of-sample predictions are used in the dynamic portfolio rebalancing over time.

Thus, the rest of the chapter is structured as follows. The second section gives a brief overview of the related research. The methodology is described in the third section, with a presentation of the results in the fourth section. The final, fifth section deals with conclusions.

2 Literature review

As the literature that focuses on stock price prediction was growing rapidly over the past couple of decades, this subsection will focus on the research that is closely linked to the topics of this chapter. In general, the autoregressive moving average (ARMA) and multivariate generalised autoregressive conditional heteroskedasticity ((M)GARCH) are probably the most popular approaches within econometrics. Some of the research that utilises these models for forecasting purposes includes the following papers (with the references within them): Mokhlis et al. (2021) or Škrinjarić (2018). There exist papers that combine some of the previously mentioned methodologies, due to exploiting benefits from different approaches. Such research includes Pai and Lin (2005), where ARIMA (integrated ARMA) is combined with vector support machines; neuro-fuzzy approach in Atsalakis and Kimon (2009); artificial neural network (ANN) with the neuro-fuzzy approach in Billah et al. (2015); data envelopment analysis (DEA) combinations with the grey methodology (Škrinjarić and Šego, 2021); etc.

One of the most related applications of the GSM approach to this one is the grey relational analysis (GRA), in which a ranking system is constructed based on the stock characteristics. The main idea is to collect relevant variables that are being used as the stock characteristics in terms of return, risk, financial ratios, and other information relevant to the investor. Then, those characteristics are used to rank stocks every day, week, month, etc. The idea is that the investor has to compare many stocks based on many criteria, so it is hard to obtain a ranking system manually. The GRA comes into play, as it is, in essence, similar to the DEA in that it constructs a score for every stock, with the greater the value of a score is, the better stock performs. However, the approach in constructing such a score is different from the efficiency score within the DEA. Here, we include the following research. Škrinjarić and Šego (2021) combine the DEA and GRA approaches to evaluate the business performance of 21 stocks. This was a static analysis as the financial ratios data were included for the last quarter in the time the study was written. The DEA results were compared to the GRA results in terms of ranks, and portfolio investing advice was given. However, such analysis could be done every quarter at best, with a lag in time regarding portfolio investing. Next, Škrinjarić (2019) combined the GRA approach with the fuzzy logic in-stock selection process. Here, the author uses market data to rank stocks every week. The GRA rankings were used to form membership functions in the fuzzy logic approach. Dynamic analysis can be thus made, to do portfolio rebalancing over time.

Often, the research does not include the variables which are important for the investor in terms of portfolio utility theory. But this was corrected in Škrinjarić (2020), in which the author utilises variables that are most relevant in the utility theory for the GRA ranking system. Accuracy rates of the classification of company performance were compared for DEA and GRA in Fang-Ming and Wang-Ching (2010), but the authors here focused only on the companies in the electronics sector. Chen et al. (2014) observed macro aspects of predicting stock returns within the ANN and GRA approaches, which can be used for macroeconomic policies. Such studies are very useful for economic policymakers, but they are not so much related to our goals. Interested readers can refer to the mentioned study for other references. Bayramoglu and Hamzacebi (2016) focused on the GRA approach to rank selected nine stocks on the Turkish stock market as a simple application of this methodology. There is a lack of investment strategy simulation found, which could be helpful for investors.

However, the GRA approach uses data from the past to make decisions about future investments. That is why we focus more on the grey models (GMs), as they are used in forecasting the future price movement. Some earlier work can be found in Doryab and Salehi (2018). Some of the newer studies include Zou and Zhou (2009), in which authors observe a GM for intraday price prediction and show that it is reasonable to use this method for stock price prediction; Kayacan et al. (2010), where authors compare several GMs in fitting and forecasting stock prices; and Faghih Mohammadi Jalali and Heidari (2020), where authors focus on Bitcoin prices by applying the GM(1,1), which is something new compared to usual applications of GMs on typical stock prices. However, many of these studies just compare the out-of-sample forecast errors. Investors are interested in the application of the results. That is why some studies focus on these issues: Škrinjarić and Čižmešija (2021) compared GMs (1,1) and (2,1) with some typical econometric models of forecasting. The grey approach was best in out-of-sample forecasts, not only by comparing the forecasting errors, but when simulating trading strategies in which decisions were made based on the forecasts from each model, and Škrinjarić and Šego (2019) did a similar study, in which other popular non-grey approaches were compared to the grey approach, and similar results were obtained. Other time series were examined via the GM approach as well, such as property prices in Tan et al. (2017). However, the majority of existing papers focus on the methodological details. Empirical applications for potential investors are lacking. Thus, this chapter aims to fill that gap.

3 Methodology description

For the description of the methodology, we follow Liu et al. (2016) and Liu and Lin (2006, 2010). In essence, the GMs are differential equations that are used for forecasting future values. However, the time series which is observed within this methodology has to have certain characteristics, such as being a positive sequence of numbers. That is why GMs are used for stock prices, and not return series.

In essence, the basic first-order differential equation with constant parameters a and b, $a, b \in \mathbb{R}$ is given as:

$$\frac{dy}{dt} + ay = b, \tag{1}$$

where $\frac{dy}{dt}$ is the first-order derivative of function $y = y(t)$. The time path $y(t)$ is the unknown function, and it is the solution to (1). In GM literature, the time path $y(t)$ is the background value. This value has to be positive, it consists of grey numbers, and the information density of this value is infinite. The latter means that when $\Delta t \to 0$, it holds that $y(t + \Delta t) \neq y(t)$. Finally, the derivative $\frac{dy}{dt}$ satisfies the horizontal mapping. Based on these characteristics and equation (1), the GM equation can be formed as follows.

An observed time series is a sequence $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$, in which every member is a non-negative number, with $n \geq 4$. The new sequence, which is defined from the first one $X^{(0)}$, is called the first-order accumulated generating operation, AGO, as the following one: $X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\}$, in which new members are the cumulative sums defined as: $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$. In that way, the original series is smoothed out. As the AGO sequence is monotonically increasing (due to $x^{(1)}(k) > 0$ holding for every k), now the positive background value of y in (1) is satisfied as a condition. Now, the mean sequence needs to be calculated from the AGO sequence as the moving average values: $Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\}$, where it holds that

$$z^{(1)}(k) = \frac{1}{2}\left[x^{(1)}(k) + x^{(0)}(k-1)\right] \tag{2}$$

Now, the horizontal mapping condition holds as well and the following GM equation can be formed:

$$x^{(0)}(k) + az^{(0)}(k) = b \tag{3}$$

Model (3) is the Grey Model, GM (1,1) – in which the first unit value is the order of the differential equation and the second unit value is the number of variables which explain the variable x. The usual approach can be applied in solving the equation in (3), as it is just an ordinary difference equation with constant parameters. The time path is the solution:

$$x^{(0)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)}(1 - e^{a}) \tag{4}$$

This solution is used to forecast future values of $x^{(0)}$. The forecast can be static, i.e. using the same values of estimated parameters of a and b in (4), or new values could be re-estimated on a rolling-window basis. This approach is more useful for dynamic changes in the stock markets. Thus, we will re-estimate equation (3) on a rolling-window basis, in which a 30-day window will be the length.

4 Empirical analysis

4.1 Data description

For the purpose of the empirical analysis, daily data were collected for the Croatian stock market index (CROBEX), for the period from 2 January 2020 to 3 December 2020 from Investing (2020). Basic descriptive statistics

Table 1.1 Descriptive statistics of CROBEX and return on CROBEX

Measure	*CROBEX*	*Return*
Average	1620.598	–0.001
Standard deviation	112.458	0.016
Min	1364.98	–0.107
Max	2032.21	0.056

Source: author's calculation

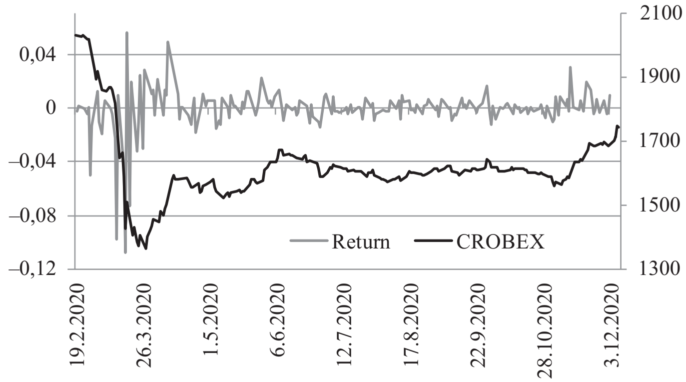

Figure 1.1 CROBEX value over time (black line, left axis), return on CROBEX (grey line, right axis).

for the index value and the return series[1] are given in Table 1.1, with the variables shown in Figure 1.1. The COVID-19 crisis, which hit all of the financial markets around the world, is visible at the beginning of the year, both in the value of the index and in the return series. Afterwards, the values are more or less stationary.

4.2 Estimation results

The dynamic approach was made in estimating formula (3), via a rolling-window approach, in which the length of the window is 30 working days.[2] Thus, based on formula (x), for every window, we estimate parameters a and b, and the one-step-ahead forecast is made based on formula (3). In order to compare the forecasting capabilities of the GM in portfolio management, three other often-used approaches are made as follows. The exponential smoothing approach is the first one, with the Holt (1957) and Winters (1960) approaches, without a seasonal component, as the season is not detected in the data. Again, the rolling-window approach is made so that the out-of-sample forecasts can be comparable. The third approach is one of the most popular ones (Lo et al., 2000; Achels, 2001) within the technical analysis, the moving average approach. Here, the 30-day moving average is calculated for the out-of-sample forecast. The summary of all approaches is given in Table 1.2.

The estimated out-of-sample values for all three approaches are shown in Figure 1.2, where we compare them to the true value of the CROBEX. Although the smoothing approach is the best fitting over the entire period, it becomes very poor at the end of the sample, when the true value has

Table 1.2 Summarisation of selected estimation approaches

Abbreviation	*Description*
GM	Grey model – 30-day rolling-window estimation of model in formula (3). One-step out-of-sample forecast is made for the decision-making process. The estimation windows are overlapping.
MA	Moving Average – rolling-window estimation of the 30-day average value of CROBEX index. Average price on day *t* is calculated as the mean price based on previous 30 days. The MA values thus have overlapping windows.
Smoothing	Holt and Winters exponential smoothing, in which the level value of the variable (i.e. the index CROBEX) is smoothed, as well as the trend in the observed variable. The smoothing parameters and details can be found in Chatfield et al. (2001).

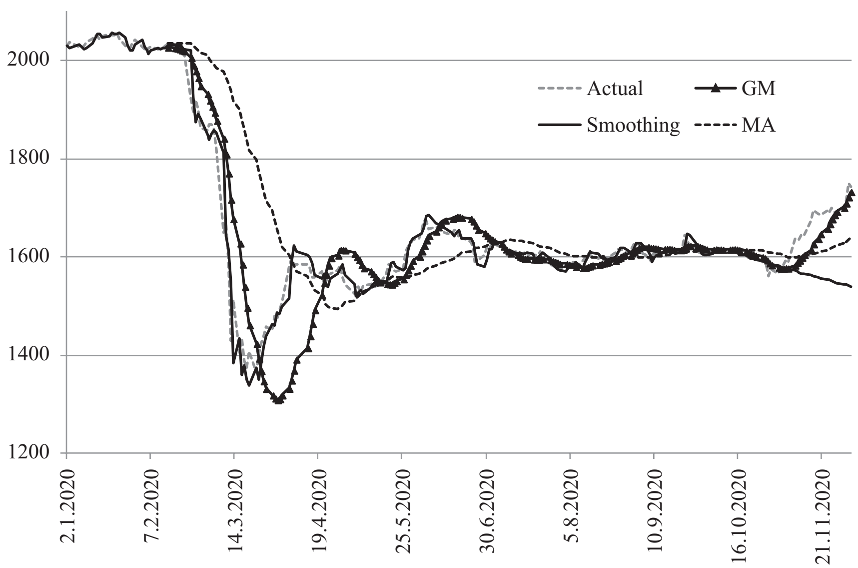

Figure 1.2 Out-of-sample forecasts of three approaches from Table 1.2.
Source: author's calculation.

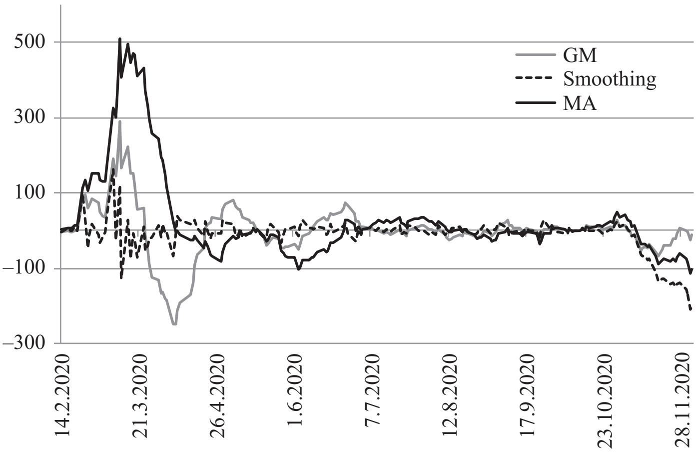

Figure 1.3 Estimation error for out-of-sample forecasts of three approaches in Figure 1.2.
Source: author's calculation.

started to increase at a rapid speed. Thus, the smoothing approach is not reliable when abrupt changes occur in the market. Next, the MA approach is unfortunately too late in detecting the changes in the market. Finally, the GM approach is a bit too late in the first part of the sample, but in the second part, it starts to pick up and it is the only one to capture the increase of the index at the end of the observed sample. Thus, the difficult task of accurate forecasting (Vlah Jerić, 2020) represents a problem for many different approaches. The forecasting error for all approaches is given in Figure 1.3. Again, as previously mentioned, the problems with all three approaches are most prominent at the beginning of the observed period. The GM approach is the best performing in the sub-period starting from July 2020 until the end of the observed sample. However, the results here show that maybe future work should focus on the abrupt changes in markets and which approach would be the best in capturing such dynamics, as here we see the majority of problems.

4.3 Trading simulation results

Next, for the purpose of using the previous results, several trading strategies have been simulated. In that way, the successfulness of using any of the previous approaches can be observed in real applications. In all strategies, it is assumed that the investor starts with one monetary unit of portfolio value. The first part of the simulation was done based on no transaction costs. The investor starts with out-of-sample one-step forecasts for all three strategies. He compares the forecasted value for day t of every strategy and compares this value to the true value of CROBEX from day $t-1$, i.e. the previous day. If the modelling result indicates that the value of the index will be greater on day t, the investor buys the index on the previous day and sells it on day t. The opposite is true if the investor determines that the forecasted value on day t will be lower compared to the true value from the previous day. Next, if the investor has sold the portfolio on day t, and he forecasts the next day's value will be greater than the value on day t, the profit investor makes from selling the portfolio is reinvested on day t so that it can be sold on the next day. Finally, if the investor has bought the portfolio on day t and he forecasts that the next day's value will be smaller than today's, the investor holds the portfolio until the opposite is true.

Based on the described strategies, the true value of the portfolio is constructed over time, for all three approaches. In that way, the true performance can be observed for all of them. To summarise, the investor is using forecasted values to form a strategy. However, the true performance of every strategy is being constructed on true return values of the CROBEX for everyday t in the observed period.

The portfolio values for all simulated strategies are shown in Figure 1.4. Moreover, they are compared to a simple buy and hold strategy as one of the often-used benchmarks in strategy comparisons. The best-performing strategy overall was the GM approach, as the majority of the time, the value of the portfolio was not only above the unit value, but the value was greater compared to other portfolio values. Furthermore, the value did not decline

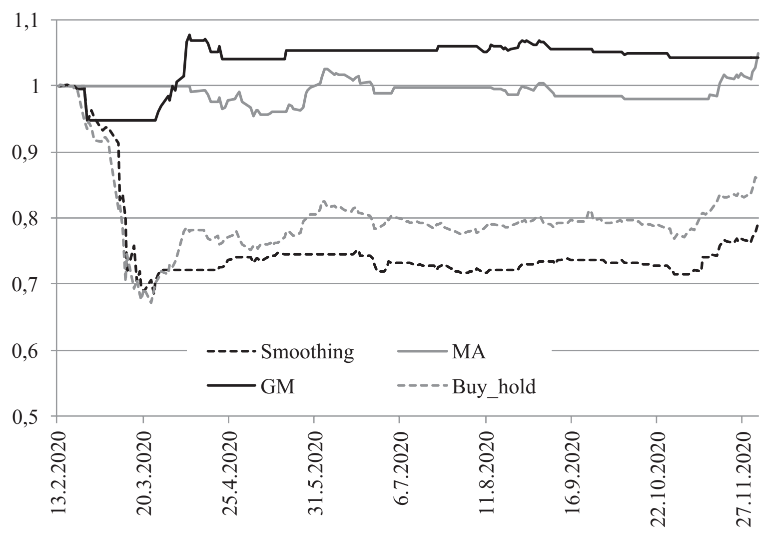

Figure 1.4 Simulated portfolio values for all strategies, no transaction costs.
Source: author's calculation.

substantially at the beginning of the period, when the whole market was going down. Similar is true for the MA strategy, but its value was worse than the GM one in the majority of cases. The buy and hold strategy although does not include any effort to analyse the market, performed poorly, as well as the smoothing strategy. Thus, this is the first confirmation of the usefulness of the GM methodology being reliable in forecasting future values of the stock prices so that this approach can be used in establishing dynamic portfolio selection, i.e. rebalancing over time.

However, the investors are facing transaction costs every time they rebalance their portfolios. Thus, all of the previous strategies, except for the buy and hold one, have been re-simulated with the inclusion of such costs. It is assumed that every time the investor buys or sells the portfolio, transaction costs have to be paid. The values have been estimated from a value of 1% per each transaction to 10%. In that way, better conclusions can be made, based on a more realistic approach. Thus, the new portfolio values, corrected for the transaction costs, are shown in Figure 1.5. The buy and hold strategy is the unchanged one over the entire period, besides the initial buy and final sell. Other strategies have varying values over time. Significant drops in the portfolio value are found every time the portfolio is bought or sold. The GM models are the best-performing ones overall again.

As the investor is interested in overall portfolio performance, not only the portfolio value over time, several measures of portfolio performance have been calculated for the observed period. The results are given in Table 1.3.

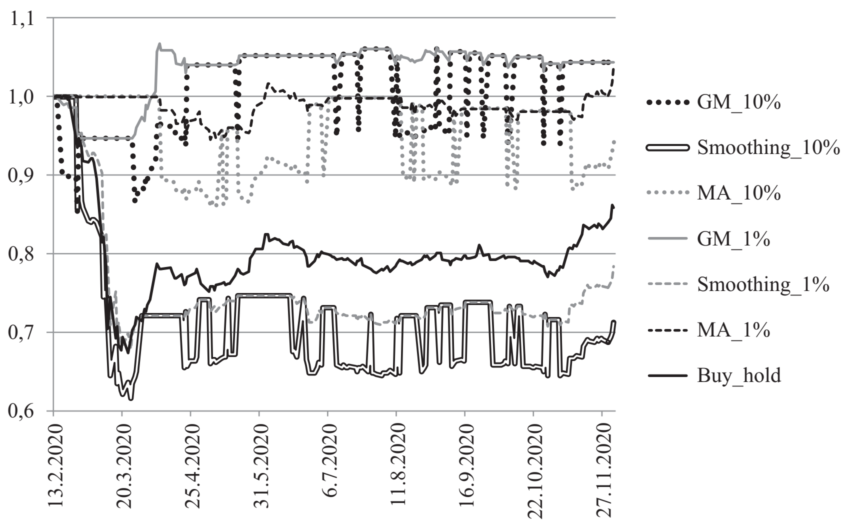

Figure 1.5 Simulated portfolio values for all strategies, included transaction costs.
Source: author's calculation.

Table 1.3 Portfolio performance of simulated strategies

Measure/strategy	*GM_10%*	*Smoothing_10%*	*MA_10%*	*GM_1%*	*Smoothing_1%*	*MA_1%*
Average return, %	**0.021**	–0.167	–0.029	**0.021**	–0.120	0.018
Total return, %	**4.27**	–33.82	–5.80	**4.27**	–24.29	3.73
Standard deviation, %	3.800	4.802	**3.414**	0.698	1.550	**0.566**
Realised volatility	0.5401	0.6829	**0.4853**	0.0992	0.2210	**0.0804**
CE[3] 1	**–0.00051**	–0.00282	–0.00087	**0.00019**	–0.00132	0.00017
CE 5	–0.00340	–0.00743	**–0.00320**	0.00009	–0.00180	**0.00010**
Total transaction costs	**5.5079**	8.5692	8.2461	**0.5508**	0.8569	0.8246
Return/risk	**0.0055**	–0.0347	–0.0084	0.0301	–0.0772	**0.0325**
% of non-negative returns	**84.24**	68.47	77.83	**85.22**	68.97	78.33

Note: Bolded values indicate best performance by row within the 10%, i.e. 1% transaction cots groups.
Source: author's calculation.

First of all, the average return is calculated as the mean of the realised returns corrected for transaction costs. The total return is calculated based on the final portfolio value and the unit value, which was the starting point. Standard deviation is the estimation for the risk series, as a typical risk measure, followed with the realised volatility, which was estimated via the formula $RV = \sqrt{\sum_{t=1}^{\tau} r_t^2}$ (see Andersen, 2008; Andersen and Bollerslev, 1998; Barndorff-Nielsen and Shepard, 2002). Next, total transaction costs have been summarised for every transaction; the average return over one unit of risk has been calculated as well. In the end, the certainty equivalent (CE) was estimated as a measure of the utility which an investor receives from a portfolio based on the first two moments of the portfolio return distribution (Cvitanić and Zapatero, 2004; Guidolin and Timmermann, 2008). The CE value is estimated as follows: CE $\approx E(\mu) - 0.5\gamma\sigma^2$. The $E(\mu)$ is the average portfolio value, the parameter gamma (γ) is the coefficient of absolute risk aversion, and the portfolio variance is denoted with σ^2. Finally, for every strategy, we count how many times were the return series non-negative (i.e. return series corrected for the transaction costs). The values of the return series, the return over one unit of risk, the CE values, and the percentage of time when non-negative returns were obtained should be greatest possible, whereas the risk measures and the total transaction cost should be lowest possible.

Table 1.3 is divided into two sections, as the strategies with 10% transaction costs cannot be compared to 1% costs strategies. The bolded values indicate the best performance of a strategy for the selected part of the table. When observing the strategies with 10% included transaction costs (left panel of Table 1.3), the GM one is the best performer, as it is best six times, whereas the MA strategy follows with three best-performing measures. The last one was the smoothing one. Again, the GM strategy is the best one, which confirms previous findings. Similar conclusions hold for the 1% transaction costs strategies (right panel of Table 1.3). The GM strategy is the best one again, now with five best-performing measures, followed by the MA strategy again (with four best values).

5 Conclusion

As stock price prediction remains one of the most difficult tasks in portfolio management today, this chapter aimed to analyse an approach that could be useful in obtaining such results. As the results showed that there exists potential in utilising the GM in stock price prediction, the findings here can be useful in future research and applications. First of all, the simplicity of this approach enables it to be used as a tool in practice, as it does not ask for complicated and high knowledge of the investor who is not specialised in mathematics. Other a bit complicated approaches could be used, in cooperation with someone specialised in quantitative methods. Direct interpretations of the results, in terms of comparing future price with today's real price, are also an attractive characteristic of this methodology. Thus, future work should at least include the portfolio simulation part, with the portfolio performance comparisons. In that way, investors obtain insights into real-world problems and can easily interpret the findings. A detailed analysis of the methodology could be useful for those who observe these issues on a theoretical basis. However, empirical research is still lacking, especially those that are based on finance theory.

Besides the advantages of this research, there are some pitfalls. In this study, we have focused on a stock market index as a basis for portfolio investing over time. That makes it a simple application in practice. Investors deal with many stocks at once, so such methodology should be observed in future work on a sample of stocks that would be considered by a real-life investor. This would have to include someone who is specialised in quantitative methods if such practices would be tested on the stock markets. Furthermore, the analysis in the future could be extended via other quantitative approaches, such as the generalised autoregressive conditional heteroskedasticity methodology, which is often used in modelling return and risk series simultaneously. Although many possibilities exist today to combine different models and techniques, we still advise taking a parsimonious approach whenever possible, as the over-parameterisation of models could lead to problems. If simpler approaches could obtain results just as good as more complex ones, simpler ones could have the advantage over them. This is due to investors have to deal with many data and information daily, ranging from the company's private information to the macro aspects of analysis, not one market, but different markets in different countries.

We hope that certain interesting questions have been raised and that the future work, especially the popularisation of the grey methodology, will be extended and more observed.

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Notes

1 Return series in this chapter is calculated base on the formula $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where r_t is return on day t, P_t is price, i.e. index value on day t.

2 This is an usual length of the window for estimations regarding stock markets, please see Škrinjarić (2019) and references in that paper.

3 CE denotes certainty equivalent. 1 and 5 denote the value of the gamma parameter.

2 Predicting Financial Statement Fraud using Artificial Neural Networks

Aishath Shaiha Shareef and Geetha A. Rubasundram

1 Introduction

Reported cases of financial statement fraud (FSF) are increasing daily. Deliberate management misrepresentations are resultant of poor financial performances, pressure to meet certain financial targets, absence of relevant internal controls as well as abuse of power. 'Cooking the books' has been an issue for more than a decade, affecting the company itself, shareholders, investors as well as the economy as a whole. FSF accounts for 10% of fraud cases and is worth approximately $954,000 in median losses (The Association of Certified Fraud Examiners, 2020). Current detection systems used within organizations include identifying red flags, using conventional statistical methods, outdated software techniques, whistleblower tips, internal audits and management reviews (ACFE, 2018), which may not be effective in detecting FSF. It is high time for organizations to make the most of available technologies which can identify fraud at the point of activity.

The Association of Certified Fraud Examiners (1988) defines FSF as 'an intentional, deliberate, misstatement of omission of material facts or accounting data which is misleading and when considered with all the information made available, causes the reader to change or alter his/her judgment or decisions' (ACFE, 2019). Revenue recognition was the area that had the highest vulnerability with 38%, followed by manipulation of expenses and improper disclosures of 12% where these misstatements could take months or years to be detected under the preventive systems (Deloitte Forensic Center, 2008). Weak internal controls increase the risk of FSF as top managers are often involved; thus, they have the power to override these controls (Scharfstein and Gaurf, 2013).

Artificial intelligence (AI) is known to process tasks with incredible precision and speed. Artificial neural network (ANN) is a component of AI where positive results are obtained by the use of a number of variables with complicated mutual interactions or by multiple solution groups and is the most frequently used technology in the financial field (Omar, Johari and Smith, 2017). An ANN predictive model could detect any suspicious activity, fraud or anomaly in a matter of seconds (Faraj Al-Janabi and Saeed,

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2011). ANNs can determine outcomes when multiple variables and mutual interactions are present, similar to the ways biological neural networks perform (Omar, Johari and Smith, 2017). The concept of ANN is best explained by mathematical formulations and algorithms which can be optimized through different techniques and approaches (Farizawani et al., 2020) which are commonly used to construct predictive models (Bach et al., 2018).

ANN has complex processing capabilities to develop algorithms that identify patterns and cater to a number of issues, such as predictive problems. The main advantage of ANN is its ability to work with complex and relatively large datasets (Dilek, Cakır and Aydın, 2015). With this, they are able to generalize well and present a 'real-world' solution for a given issue. They are fault tolerant, which is one of the most important factors when handling complex datasets, as they have the capability to handle fuzzy, incomplete and noisy information (Lancashire, Lemetre and Ball, 2009).

The parallel information processing capability of ANN shows that it is able to perform multiple tasks at the same time, including handling nonlinear relationships from complex datasets; this allows ANN to stand out compared to other similar technologies of conventional linear methods as they do not have these characteristics (Dilek, Cakır and Aydın, 2015). ANN is known to have distributed memory, which means that the success of the network is based on the learning process which can be taught under selected instances. The learning stage is crucial for ANN models; however, after the networks have learned, they are able to make decisions based on similar events (Mijwil, 2018).

The key reason for ANN to have gained fame within a number of different fields is because of its ability to provide highly accurate results. Although ANN models are more complex than traditional statistics and conventional linear methods, their ongoing significance due to results in a high accuracy level is remarkable (Sharma and Chopra, 2013). Due to its capabilities such as being known to present reliable predictive models, adjust to dynamic environments and have versatile characteristics, ANN has been the go-to technology, especially in the financial field (Fanning, Cogger and Srivastava, 1995). ANN is used due to its ability to present a high accuracy for predictive modeling in the financial field to detect FSF (Bulusu et al., 2020).

2 Artificial Neural Network (ANN)

The research and development of ANN had begun early in 1943 when McCulloch and Pitts studied the activities of the neurons in the human brain from a mathematical perspective. In 1949, Hebb had established a learning mechanism that identified the learning of the brain, which led Rosenblatt (1958) to construct a computational model, now known as 'perceptrons' similar to the processing elements of the brain

ANN imitates the computational capabilities of a biological neural network similar to the human brain and is organized into three layers, namely, the input layer, the hidden layer and the output layer (Koskivaara, 2004). The three layers of the ANN architecture provide the end result for the complex mathematical model. The input layer enables the intake of the independent variables, the hidden layer receives and transmits signals, while the output layer transfers the data through dependent variables (Omar, Johari and Smith, 2017). The inter-unit connection strengths called 'weights' determine the strength of the input and its processing ability. These weights are then altered through algorithms to adjust them, i.e., for learning and training to obtain the output required (Harsh, Kukreja, 2016). The application can be categorized into three stages: the functioning stage, the learning stage and the validity stage. The functioning stage introduces the said weights to work with the input and output vector. The input is transformed by an activation function such as a sigmoid or hyperbolic tangent into the output. The learning stage is where the network is trained to minimize its errors and the validation stage evaluates the errors after each learning stage and determines the number of hidden units in the neural network (Paule-Vianez, Gutiérrez-Fernández and Coca-Pérez, 2019).

Multilayer perceptron (MLP) is one of the most successful supervised learning techniques of ANN. MLP is known for its learning capacity, error tolerance, pattern recognition as well as its promising generalizability (Heidari et al., 2019). It is used to decipher complex processes of the real world and is the most used technique in the financial field. MLP is extensively used for constructing predictive models that are non-linear in nature and has complex relationships (Pham et al., 2017) which are considered very important as the output cannot propagate from the linear function of the input (Omar, Johari and Smith, 2017). MLP has been consistently used by previous researchers for FSF (Sevim and Uğurlu, 2015; Chen, 2016; Mubalaike and Adali, 2017; Omar, Johari and Smith, 2017; Elechi, 2019; Thompson, Aborisade and Odeniyi, 2019).

The architecture of MLP is categorized under the feed-forward neural networks (FFNN) and is considered a non-parametric estimator for classifying and detecting intrusions (Marius-Constantin et al., 2009; Mubalaike and Adali, 2017). The term 'feed forward' refers to it being a hierarchy that is organized by two or more neurons or layers where the interconnections of the perceptron flow in one direction from the input to the output, instead of forming a cycle (Balabanov, Zankinski and Kolev, 2018; Singh and Banerjee, 2019). The variables used for the study will be processed through the first layer called the 'input layer' which will pass through the hidden layer(s) to the final layer known as the 'output layer'. These layers are interconnected and the connections between these neurons are represented by weights that can be mathematically depicted (Alameer et al., 2019).

MLP neural networks have a number of advantages for predictive modeling, such as their outstanding ability for adaptive learning. Furthermore, no pre-assumptions exist when distributing the training dataset for the model construction and the importance of the input variables does not require any

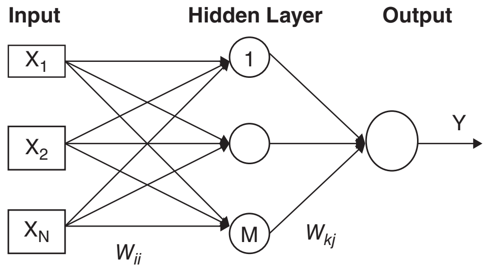

Figure 2.1 Architecture of a multi-layer feed-forward neural network.

decisions to be set (Pham et al., 2019), this eases the process of building the model with optimized function settings. The model is then activated using the backpropagation (BP) learning algorithm for supervised training of the model to be more stable and less heuristic (Aizenberg and Moraga, 2007). The architecture of a typical MLP neural network can be seen in Figure 2.1.

However, the construction of MLP networks has its fair share of problems. Firstly, failure of building a proper architecture may cause the network's predictive ability to significantly decrease and secondly, excess connections may result in the training data to be over-fitted (Castro et al., 2017).

Construction of the model requires careful consideration of a number of other factors such as interconnections and functions, which is mathematically very complex, as ANNs are. One such factor is the transfer function, also known as the 'activation function', which is the pillar of any neural network and is used to determine the weighted sum of input and biases. The transfer function introduces non-linearity within the neural network and assists in automatic learning capabilities of the connection weights (Roy et al., 2018), with the most commonly used activation functions, sigmoid and hyperbolic tangent. The sigmoid activation function is non-linear in nature and has a smooth gradient and the output of the function is in the range of (0,1). The hyperbolic tangent activation function, also known as 'tanh', has similar characteristics to sigmoid, except for, the output is in the range of (−1,1). In this research, the hyperbolic tangent activation function will be used. The formula of the sigmoid function is $\gamma(c) = 1/(1+e-^{c})$ and hyperbolic tangent function is $\gamma(c) = \tanh(c) = (e^{c}-e-^{c})/(e^{c}+e-^{c})$.

The second is the training function. In MLP networks, the BP learning algorithm is commonly used to train feed-forward neural networks in supervised learning (Karmiani et al., 2019). BP calculates the gradient of the loss function using gradient methods such as 'gradient descent' or 'scaled conjugate gradient'. The gradient descent BP algorithm, also known as the 'vanilla gradient descent algorithm', is the most popular optimization method and the steepest descent training function (Omar, Johari and Smith, 2017). It adjusts the weights in the descending gradient direction to measure the output error and calculate the gradient of error (Sharma and Venugopalan, 2014). On the other hand, conjugate gradient algorithms produce faster convergence instead of steep descent directions, and it does not carry out line search at each iteration, whereas other conjugate gradients do (Babani, Jadhav and Chaudhari, 2016).

The network can be trained in three different types, i.e., batch, online or mini-batch. Batch training uses the entire training dataset and updates the synaptic weights once all training data is passed (Burlutskiy et al., 2016). It is known to directly minimize total error and is more suitable for smaller datasets. In contrast, online and mini-batch training is used for larger and medium-sized datasets. Online training sequentially records and updates the synaptic weights after every training data is passed (Sahoo et al., 2018) while mini-batch training divides the data into groups of sizes and updates the synaptic weights for each group at a time (Xu et al., 2014). The gradient descent method is used with all three types of training, whereas the scaled conjugate gradient method applies only to batch training, and for this research, the gradient descent BP algorithm in batch training is used.

The most common measures of the error to train neural networks are mean squared error (MSE) and cross-entropy error (CE), and in this study, CE will be used. There has been speculation on both error functions comparatively, as researchers are now suggesting that CE proves to be more reliable than MSE. CE calculates the difference between two probability distributions between 0 and 1 and is known to minimize the distance. It provides better results in terms of error rates, works well with back-propagation algorithms and leads to faster convergence (Golik, Doetsch and Ney, 2013). CE can be calculated as (Nasr, Badr and Joun, 2002):

$$E_m = \frac{1}{m}\sum_{k=1}^{m}[t_k \ln y_k + (1 - t_k)\ln(1 - y_k)]$$

The output activation function for the research is 'Softmax'. This is the most frequently applied function when the error function is cross-entropy. Softmax appears in the last layer of the neural network as it turns the numeric output into probabilities by taking the exponents of each output. It then sums up the complete output by normalizing the numbers by the sum of the exponent; thus, all probabilities then add up to one (Farhadi, 2017). It is calculated by $\gamma(c_k) = \exp(c_k)/\Sigma_j \exp(c_j)$.

The construction of algorithms for neural networks requires learning from and making predictions based on the dataset provided, which is divided into training and testing. In order to ensure the model is able to perform well and generalize, it is important for the data to be split sensibly (Xu and Goodacre, 2018). Prior to separation, the dataset is sent through pre-processing to train the multilayer neural networks by the 'normalization' function. This is to allow the dataset to generalize with the inputs that will be within the range of its training data (Omar, Johari and Smith, 2017).

The separation of training and testing datasets is considered crucial in the construction of an ANN model, as this may affect its performance and end result. The training dataset determines the weights and parameters of the model and is usually larger than the testing dataset (Koskivaara, 2004). However, the customization entirely depends on the size of the available data, the underlying mechanism, the complexity of the model and the goal of the research being conducted (Mani et al., 2019).

The test data set provides the final output and validates the data for the model. It is unbiased in evaluating the model performance and has similar statistical properties and distributions as the training dataset (Koskivaara, 2004). There has been no set rule or a standard number for the distribution of the dataset into training and testing samples. Prior researchers and authors have categorized the training and testing datasets into 90:10, 80:20, 70:30 and very little on 50:50 (Ahmadlou and Adeli, 2010). It can be seen that the training set is almost always larger than the testing set, although this depends on the data characteristics and its size.

3 Methodology

The process of arriving at the final result of the ANN predictive model was through a sequence of carefully planned steps. The selected dataset was brought into SPSS Statistics and pre-processed using the 'Automatic Data Preparation' tool, optimized for accuracy. The transformed dataset was imported to ANN Multilayer Perceptron to begin with the model architecture. The first step was to categorize the covariates, normalize them and divide the data into training and testing through the 'partition' tab. The training data set was 95% and the testing dataset was set at 5%. Following this, the optimization algorithm was set at gradient descent through batch training. The functions were then selected, i.e., for the hidden layer activation function; hyperbolic tangent was opted, cross-entropy as the error function and softmax for the output layer activation function. After the architecture of the neural network was set as the optimal model, the ANN was trained and tested to arrive at the result of the final accuracy level. Figure 2.2 depicts the diagram of the entire process.

3.1 Data and Sample Selection

The sample size has a significant influence on the precision and end results of a study, where the larger the sample size, the increase on the research precision (Omidi et al., 2019). However, the sample size selected to conduct this study is based on a number of factors such as the availability of time and resources. The sample companies selected for the research follow GAAP and IFRS and verifying these accounting standards were followed was given utmost importance to ensure comparability, although some companies identified as fraudulent have the history of breach or violation.

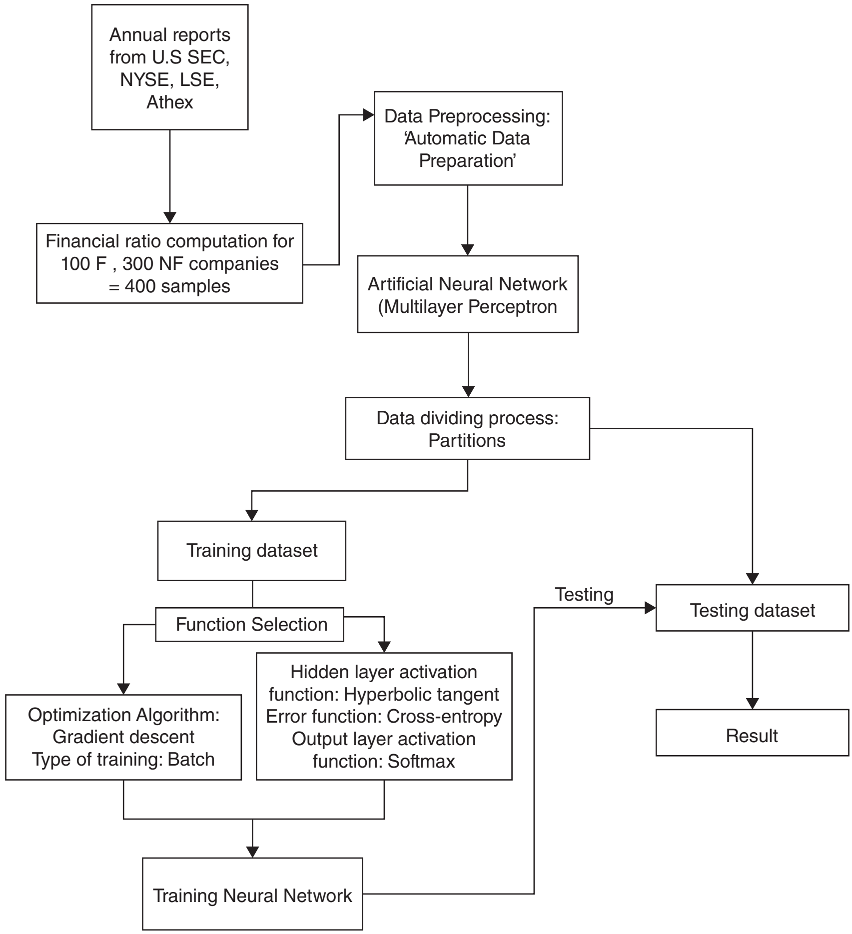

Figure 2.2 Process for the establishment of the ANN model.

Secondary data had been obtained from annual reports from the U.S. Securities and Exchange Commission (SEC), the New York Stock Exchange (NYSE), the London Stock Exchange (LSE) as well as the Athens Stock Exchange (Athex). The annual reports (10-K) of fraudulent and non-fraudulent companies from the stock exchanges were acquired and categorized under fraud (F) and non-fraud (NF). This study uses the 'Matching Sample Design Concept' by Kotsiantis et al. (2006) where one fraudulent company was matched with two non-fraudulent companies. The companies were selected based on their respective industry with a total of 50 fraudulent companies and 150 non-fraudulent companies. By adopting this method, a number of external environmental factors are managed, eliminate differences between the variables that could potentially affect the end result and strengthen the relationship between the variables (Kotsiantis et al., 2006). These companies are obtained from the manufacturing industry (15F, 45NF), the service industry (20F, 60NF), the healthcare industry (10F, 30NF) and the retail industry (5F, 15NF).

Companies that had published fraudulent and manipulated financial statements were identified based on the SEC complaints and litigation releases during the periods 2010–2018 and the data for non-fraudulent annual reports were selected randomly from the same period 2010–2018. More recent annual reports were avoided since it was difficult to confirm their accuracy and reliability as litigation claims may/may not arise in the near future.

Data were obtained for two consecutive years for each company, which resulted in a total of available data for 100 fraudulent samples and 300 non-fraudulent samples. The data were converted into the form of financial ratios as per the recommendations of past research. Prior research conducted had initially computed financial ratios to detect fraudulent financial reporting which can be seen in the journals of Koh and Tan (1999), Spathis (2002), Persons (2011), Omar, Johari and Smith (2017), Rahman, Deliana and Rihaney (2020), Fitri, Syukur and Justisa (2019) and Nakashima (2017).

The financial ratios were selected according to the fraud risk indicators suggested by ISA 240 (IFAC, 2009) and categorized under profitability ratios, solvency ratios and asset turnover ratios which were found to be the most fraud sensitive (Kanapickienė and Grundienė, 2015). A total of eight financial ratios have been selected as the research variables to construct the model using ANN to detect FSF and the reason for minimizing the number of variables is to ensure its' stability and generalizability (Omar, Johari and Smith, 2017). This is in line with the elements in the fraud triangle, a model developed by Dr. Donald Cressey, a criminologist in 1953. The concept was first introduced in his research for 'Other People's Money: A Study in the Social Psychology of Embezzlement' asking the pertinent question of 'Why do people commit fraud?'. This coined the ever famous 'fraud triangle', a useful framework that identifies high-risk fraud situations and is commonly used in organizations as a fraud identification mechanism and particularly popular when performing audits (Huang et al., 2017). According to Cressey, the three factors of (1) pressure, (2) perceived opportunity and (3) rationalization must be present for a person to commit the fraudulent activity (Nakashima, 2017). It is believed that these three elements are dependent on each other and are resultant of individual organizational behavior and systems (Al-Jumeily et al., 2016).

The dimensions of the fraud triangle are as follows:

1 Pressure

Pressure is defined as the motivation or incentive for the perpetrator to engage in the fraudulent activity. It can arise from economical demands and a lavish lifestyle, financial problems and necessities or even external pressures such as company financial targets (Rahman, Deliana and Rihaney, 2020). There are four variables that can further explain pressure, i.e., (a) Financial stability: the company experiences financial problems as a result of economic conditions or by its operations; (b) Leverage: it is a ratio that measures the amount of debt compared to the company's equity. It gives an overview of the capital structure of the company to evaluate its overall health; (c) Financial targets: this is where individuals face the pressure to achieve goals set by the management or internal parties (Rahmawati and Kassim, 2020). As per SAS No.99, financial stability, external pressure, personal financial needs as well as company financial targets are common conditions that fall under 'pressure' (Pramana et al., 2019). There are a number of indicators for pressure such as solvency issues, the threat of bankruptcy and investor's withdrawals. According to fraud risk factors from the ISA 240, operating losses lead to a threat of bankruptcy or foreclosure, leading to management pressure on FSF. Similarly, solvency issues could lead to manipulation of the company's financial statements as it poses a risk for investors to withdraw their investment from the company (IFAC, 2009), which further pressures the management to engage in FSF. In this research, the use of solvency ratios as fraud risk indicators that are under the element of pressure is used. The solvency ratios will represent the ability of the company to pay back the short and long-term debt and borrowings, i.e., the liquidation of the company (Izzalqurny, Subroto and Ghofar, 2019). The financial ratios used under 'pressure' are total debt/total assets and debt/equity.

2 Opportunity

Opportunity refers to situations or circumstances that allow fraudulent activities to occur. This will be achieved once the individual finds a way to abuse his position of trust with usually a low risk of getting caught (ACFE, 2016). According to SAS No. 99, opportunities to carry out fraud usually arise when the company has weak internal controls, poor workplace conditions, a lack of proper supervision or an ineffective organizational structure (Pramana et al., 2019; Rahman, Deliana and Rihaney, 2020). In order to minimize the opportunities to carry out the fraud, it is important for the board of directors to monitor and oversee the performance of the company as well as ensure proper internal control systems are in place (Rahmawati and Kassim, 2020). According to the fraud risk factors from ISA 240, ineffective monitoring by the management and accounts that are difficult to corroborate such as those that require subjective judgment and uncertainties are placed under the fraud triangle 'opportunity'. Accounts that are easily manipulated include inventory items that are small in size, cash, receivable entries and other forms of misappropriation of assets (IFAC, 2009). In this research, asset turnover ratios from the fraud risk indicators are used with the 'opportunity' element of the fraud triangle. Asset turnover ratios measure the value of the company's sales with respect to its assets through variables such as inventory and receivables. These variables are commonly overstated in company accounts, which increases the risk of FSF (Somayyeh, 2015). Furthermore, in this research, the logarithm of total assets, i.e., the firm size, is used as a component that would normalize and stabilize the variances in this study (Omar, Johari and Smith, 2017). The financial ratios that are computed under the element of 'opportunity' from the fraud triangle are receivables/sales, inventory/sales and logarithm of total assets.

3 Rationalization

Rationalization refers to the ability to justify and provide reasoning for unethical acts. Rationalization is portrayed by a person's character, attitude or their ethical values (Pramana et al., 2019). It deals with the individual's state of mind and the motive behind their behavior (Omar, Johari and Smith, 2017) to carry out the fraudulent activity. It is difficult to identify as it involves deeper emotions and justifications. It is common for the perpetrator to rationalize stating that it is for the company's benefit or that the top management does not follow integrity nor ethical values (Hermawati, 2021). The fraudsters find justifications to try and make their activities acceptable and often give excuses such as it being common within the company including the management or it being the last resort for personal financial difficulties (ACFE, 2016). According to ISA 240, the entity's ethical values and standards play an active role in the individual's decision to carry out fraud. Companies that have a known history of breaches and violations are often found to repeat these actions. The most common way of manipulating financial statements under the rationalization element is by presenting a higher profitability level. The motive behind this is to attract existing and potential investors and to hold the company's reputability (IFAC, 2009). In this research, profitability ratios are used according to the fraud risk indicators under the 'rationalization' component. Profitability ratios indicate the company's ability to generate profits and are often related to the increased risk of FSF if the levels of profits of a company are low (Izzalqurny, Subroto and Ghofar, 2019). The financial ratios computed are sales/total assets, net profit/sales and net profit/total assets.

In Malaysia, Omar, Johari and Smith (2017) applied the fraud triangle as their theoretical framework to predict FSF. The study was based on small-market capitalization companies from Malaysia and the components of the fraud triangle were used for variable selection of the model using ANNs. The variables were computed based on the fraud risk indicators and ten financial ratios were used and categorized under pressure (solvency ratios), opportunity (turnover ratios) and rationalization (profitability ratios) (Omar, Johari and Smith, 2017). Fitri, Syukur and Justisa (2019) reported that companies with fraudulent activities had faced 'pressure' for financial stability, 'opportunity' due to increased transactions with related parties and 'rationalization' by frequently changing company auditors (Fitri, Syukur and Justisa, 2019). Nakashima (2017) reported that pressure due to financial targets and opportunities due to ineffective governance and management discretions (Nakashima, 2017) contributed to a higher risk of FSF when assessing 280 Japanese public companies.

3.2 Data Processing

Once the financial ratios were computed and fed into the model, the dataset was pre-processed using the 'Automatic Data Preparation tool' in SPSS Statistics, with 'optimize for accuracy'. The transformed variables were then used to construct the model using the multilayer feed-forward neural network with one hidden layer. The input totaled up to 12 units and the rescaling method was 'normalized'. The hidden layer activation function used was a hyperbolic tangent and the number of units in the hidden layer adds up to seven. The output layer activation function used was softmax with the error function; cross-entropy and the number of units was two. Figures 2.4 and 2.5 show the architecture of the neural network as well as the network information.

The function selection for the architecture of the neural network was carefully considered. As per Figure 2.3, after partitioning the training and testing dataset into 95:05, the optimization algorithm was set at gradient descent for batch training. The learning initial rate was 0.4, the momentum was 0.9, the interval off center was 0.5, the error change was 1.0E−4 and the epochs were set at 'auto'. At the training stage, the stopping rule used was one consecutive step with no decrease in error and at the testing stage, the CE was 17.030 with an average incorrect prediction of 0.067.

Case Processing Summary

		N	Percent
Sample	Training	380	95.0%
	Testing	20	5.0%
Valid		400	100.0%
Excluded		0	
Total		400	

Figure 2.3 Partitioning of training and testing dataset.

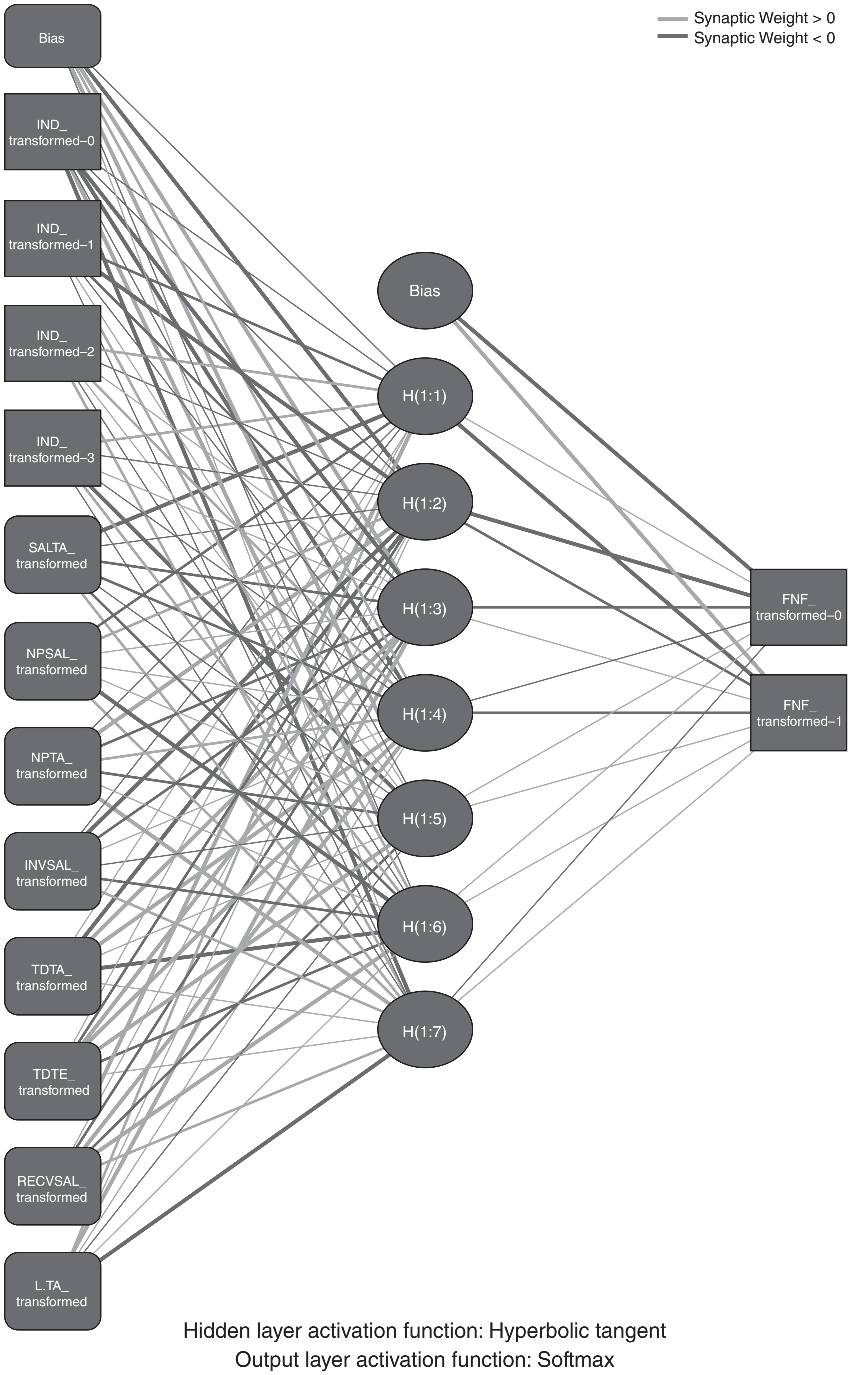

Figure 2.4 Architecture of the multilayer feed-forward neural network.

Network Information

Input Layer	Factors	1	IND_transformed
	Covariates	1	SALTA_transformed
		2	NPSAL_transformed
		3	NPTA_transformed
		4	INVSAL_transformed
		5	TDTA_transformed
		6	TDTE_transformed
		7	RECVSAL_transformed
		8	L.TA_transformed
	Number of Units[a]		12
	Rescaling Method for Covariates		Normalized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	FNF_transformed
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross–entropy

a. Excluding the bias unit

Figure 2.5 Network information.

4 Results and Discussion

F /NF

		Predicted		
Sample	Observed	F	NF	Percent Correct
Training	F	4	94	4.1%
	NF	2	267	99.3%
	Overall Percent	1.6%	98.4%	73.8%
Testing	F	0	2	0.0%
	NF	0	28	100.0%
	Overall Percent	0.0%	100.0%	93.3%

Figure 2.6 Classification of ANN.

Overall Percent Correct

Sample	Overall Percent Correct
Training	73.8%
Testing	93.3%

Figure 2.7 Overall percent correct.

The results show that ANN was able to predict FSF with an accuracy level of 93.3%. The findings reflect a similar and consistent range of accuracy to past studies such as 93.7% (Temponeras et al., 2019), 97% (Elechi, 2019), 97.3% (Paule-Vianez, Gutiérrez-Fernández and Coca-Pérez, 2019), 98% (Shenfield, Day and Ayesh, 2018) and 94.87% (Omar, Johari and Smith, 2017) (Figures 2.6 and 2.7).

Hence, this reflects the predictive accuracy of this model. One of the main contributions from this research in comparison to the other researchers is that prior researchers have focused their study on one particular country or industry and do not show compilations of three or more countries. For instance, Omar, Johari and Smith (2017) had constructed an ANN model using small-market capitalization companies based in Malaysia, Chen (2016) had developed a fraud detection model using a number of data mining techniques using Taiwan's listed and OTC companies, Chimonaki et al. (2019) studies on FSF detection using data from the Athens Stock exchange while Ma et al. (2019) based the study on China, using data available from the Cathay financial database. Prior research has not combined multiple countries and was limited to one particular country and its stock exchange. Therefore, this research identified enhances the generalizability and ensures a more reliable model with a wider scope which would make it a valuable tool to perhaps synchronize anti-FSF efforts across industries and countries.

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3 Bank Network Credit Model and Risk Management System Based on Big Data Technology

Tielin He

1 Introduction

In today's 21st century, the development of big data technology is very rapid, and all walks of life in society are continuing to popularize big data technology, and people's lives are increasingly affected by big data [1]. Many computer science and technology products, such as mobile phone systems, computer systems, network social platforms, etc., will generate a lot of data on the platform system while people are using it. The application of big data has participated in many areas of human life. Big data is driving the traditional financial industry to the intelligent era, which can not only provide assistance for financial business transformation, but also innovate financial business models [2]. The application of big data technology in the bank's online credit risk system can greatly help the risk system's anti-risk ability, which can effectively reduce the risk of online credit business and prevent the emergence of non-performing assets. However, big data technology is a brand-new technology that has not been used in my country for a long time. A mature system has not yet been developed. There are many problems in practical applications, such as infringement of customer privacy and difficulty in control, which has a great adverse effect on the application of big data in various fields. Therefore, the use of big data technology to strengthen the research on bank credit risk management has strong practical significance [3].

Guohua Chen pointed out that with the development of computer information technology, network finance based on computer technology has become a current hot topic and quickly penetrated into the banking industry, which has had a certain impact on the deposit business, loan business and intermediary business of commercial banks, affect the profitability of banks. Due to poor risk control and supervision, computer internet finance has experienced a wave of credit crises [4]. Hangjun Zhou believes that technologies related to the Internet of Things have been applied to the financial field, and the data generated has been used to improve the financial credit risk management capabilities of bank loans. To date, financial credit risk is one of the most significant risks that commercial banks must face.

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However, traditional statistical models and neural network models may not be able to run fair enough or accurately to use these diversified data for credit risk assessment. Therefore, it is actually necessary to build a more powerful risk prediction model based on big data analysis and use artificial intelligence to predict default behavior with better accuracy and ability [5]. Weiwei Qiu believes that there are many financial credit risks in modern society, the most important of which is the financial risks on the mobile Internet. With the popularization of mobile payment, financial risks have also greatly increased, which makes traditional statistics and models unable to fully meet the needs of the development of modern society. Therefore, a more powerful artificial intelligence risk prediction model is needed to predict default behaviors with good accuracy and competency-based big data analysis [6].

This chapter uses big data to conduct online credit risk management based on a large amount of long-term credit and capital flow data information, and designs a more complete credit system that can provide users with more efficient loans under lower risks and match the loan time limit. China is also more precise and completes the flow of funds better. This chapter mainly starts with the establishment, development, and basic overview of bank A, analyzes the scale structure and industry status of bank A based on a more detailed data system, and further elaborates the scale and development overview of bank A's online credit business [7]. On this basis, by introducing the basis of bank credit risk and bank credit risk management theory, the current situation of bank A's network credit risk management system is analyzed, starting from the current situation of bank A's development, and the causes of bank A's non-performing loans analyzed.

2 Analysis Method of Bank Network Credit Model and Risk Management System Based on Big Data Technology

2.1 A Bank Network Credit Business

Different from other large- and medium-sized state-owned commercial banks, bank A has paid great attention to financial services since its establishment [6]. At present, bank A has basically established a comprehensive and separate risk management system. In the management system, it is divided into three levels: the head office, the first-level branch, and the second-level branch. In the decision-making of the risk system, the board of directors, the board of supervisors, and the committee are at the highest level. The board of directors has the final decision-making power. Under the board of directors, a committee is set up to carry out risk management. At the same time, under the supervision of the board of supervisors, the board of supervisors implements the president responsibility system. The head office establishes a risk management and internal control committee and implements the president's responsibility system, under which a chief risk officer is responsible to the president. The chief risk officer is solely responsible for the measurement, monitoring, and credit approval of various risks of the whole bank and is responsible to the president of the bank. The bank is responsible for the measurement, monitoring, and credit approval of various risks and is responsible to the bank president [4]. The first-level branch mainly has a director who manages the risk department and credit department of the first-level branch. The director is managed by the head office and implements the relevant regulations and requirements of the head office for risk management. The second-level branch has one head, which mainly manages the risk department and credit department of the second-level branch, and is managed by the first-level branch to implement relevant risk decisions at the higher level.

2.2 Application of Big Data in Online Credit

In recent years, the application of big data in online credit risk control has become more and more mature. Due to its fixed operating system, wide-ranging business coverage, and weak innovation capabilities, my country's commercial banks have lowered the level of application of big data in the banking business to foreign countries; however, some domestic financial technology companies make full use of technological advantages to realize a new financing model with low entry barriers for lenders, loose borrowing conditions, fast lending speed, and flexible repayment methods [8]. Online credit is the business with the highest proportion of financing for financial technology companies. For big data technology, financial companies should make use of it as much as possible, so that they can create a brand-new financial ecosystem and allow their own business to develop better. This also indicates that in the big data credit risk control, my country's online credit risk control started late and the innate credit system is missing, which can also be transformed into a late-comer advantage. In big data technology, a large amount of useful information can be obtained with only a small entrance [9, 10]. Moreover, this information is considered to be unmodifiable and protected, which saves the user the trouble of inputting a large amount of information, and also avoids the problem of information error or information fraud.

2.3 Analysis of Bank A's Network Credit Model

The production process of a bank can be divided into two parts. The employees and fixed assets in the first stage are inputs, and the output is deposits; the inputs in the second stage are deposits, and the output is loans and other profitable assets. But in these two processes, it can always be found that deposits are both output and input, which is a relatively special variable. In the network method, it is divided into two stages, that is, the first stage is used as the output meter, and the second stage is used as the input variable. The objective function of these two stages is:

The efficiency structure of input–output-oriented online banking:

$$\begin{cases} \sum_{j=1}^{n} ð_j FA_j \le \varepsilon_k FA_k \\ \sum_{j=1}^{n} ð_j E_j \le \varepsilon_k E_k \\ C_j \ge 0; j = 1,2 \cdots n; 0 \le \varepsilon_k \le 1 \end{cases} \tag{1}$$

The efficiency structure of output–input-led online banking:

$$\begin{cases} \sum_{j=1}^{n} ð_j FA_j \le C_k FA_k \\ \sum_{j=1}^{n} ð_j E_j \le C_k E_k \\ C_j \ge 0; j = 1,2 \cdots n; 0 \le \varepsilon_k \le 1 \end{cases} \tag{2}$$

3 Analysis Process of Bank Network Credit Model and Risk Management System Based on Big Data Technology

3.1 Design of A Bank's Network Credit Risk Prevention System

As an organization's internal management process, risk early warning refers to the adoption of a certain method to analyze changes in the internal and external environment before the emergence of risks, and timely measures to avoid risks, so as to achieve the purpose of risk control. The risk early warning system is a systematic project including signal sending, rapid response, risk assessment, and action plan, including multiple links. In specific operations, bank A must establish a complete operating mechanism from the initiation of the early warning to the removal of the early warning. For the overdue business, a risk warning must be initiated within 30 days, the warning must be accurately described, and a special person must be appointed to deal with it. Furthermore, after the early warning is initiated, the positions involved in the process shall promptly identify and report the different levels of early warning within the prescribed time limit. At the same time, for the early warning items that have been processed, the responsible employees should take preventive measures in a timely manner to control risks as much as possible to prevent further expansion of risks. For the early warning items that have been processed, if they no longer constitute a risk or the risk items have died out, they must be removed within five working days. Yes, to optimize the risk early warning system, the most important thing is to establish a complete indicator system, which is the basis of early warning management. According to the current business development of bank A, the indicator system can be established from both macro and micro perspectives. Among them, the macro-level should pay attention to industry and regional policy changes, and the micro-level should be as detailed as possible in the credit management process, to minimize the risk of occurrences. At the same time, it is necessary to gradually increase the proportion of quantitative indicators.

3.2 Design of the Internal Evaluation and Identification System of Bank A's Network Credit Risk

The current internal credit rating methods and methods of bank A are mainly based on qualitative analysis, coupled with certain quantitative analysis, comprehensively evaluating customers' assets, credit, and production and operation conditions, and finally forming customer credit ratings. Although this rating model combines many factors, it also has its limitations. For example, the components of qualitative indicators are too large, and quantitative indicators rely too much on financial indicators. The requirements for historical data are very high, and it is difficult to reflect the future development status of the enterprise, which leads to unsatisfactory credit rating results. At present, most commercial banks use credit ratings to control risks and evaluate customer requirements as accurately as possible to ensure the high quality of customers. Operational risk is one of the main risks faced by commercial banks. Bank A has more prominent problems in operational risk management. Limited by industry experience and the professional level of its employees, banks are still at a relatively low level in operational risk management. At present, the management of operational risk is scattered among various business units and management departments, and the management of operational risk is relatively loose. However, operational risk runs through the entire process of credit business, so the management of operational risk must go deep into specific positions, processes and nodes to achieve comprehensive and multi-angle control. Market risk management is particularly important in the context of the current increasingly complex domestic and international situations and the continuous advancement of interest rates. If bank A cannot change its traditional business philosophy and change its business model, it is bound to be impacted by the market. Improving the market risk management system is of great significance to the long-term development of bank A.

3.3 Design of Bank A's Network Credit Risk Mitigation System

Establish a loan insurance system. The loan guarantor system is one of the effective ways for banks to transfer risks. Another effective way of risk transfer is loan risk insurance. Bank A can require the loan company to pay a certain fee to the insurance company to purchase the insurance for the loan project. If the loan company cannot bear its debt due to the reasons in the insurance contract, the insurance company can repay it on its behalf, thus achieving the preservation of bank assets. In this way, the risk that the bank alone bears is effectively passed on to the insurance company. As an insurance company, if companies that can absorb more loans through this business come to insure, they are also able to repay the insurance claims of individual companies. As long as the bank grants a loan, it must bear a certain amount of risk. If the risk control measures are taken properly, it will be able to obtain corresponding profits. For bank A, some risks can be predicted and prevented in advance, and some risks are difficult to predict due to the complexity of the risks themselves and the influence of external factors. For risks that can be predicted and prevented, risk ratings can be based on historical experience and historical data, the probability and form of possible defaults can be predicted, and corresponding preventive measures can be taken in advance. For unpredictable risks, banks must take certain measures when issuing loans, such as charging fees to reduce risks, and at the same time rely on their own capital or withdraw loans for bad debts to compensate. Therefore, bank A must establish a complete risk compensation system, and at the same time pay attention to spreading loans as much as possible, in order to reduce the loss caused by unpredictable risks.

4 Analysis of Relevant Indicators of Bank A's Online Credit Risk Management

4.1 Analyzing the Changes in the Total Deposits and Loans of Bank A in the Past Four Years, the Results Are Shown in Table 3.1 and Figure 3.1

As shown in Table 3.1 and Figure 3.1, it reflects the annual report of bank A's deposit and loan growth rate in the past four years. At present, the difference between bank A's deposits and loans is mainly expressed in the form of

Table 3.1 Changes in total deposits and loans of bank A in the past four years

Year	*Deposit growth rate (%)*	*Loan growth (%)*
2017	17	13
2018	16	9
2019	14	11
2020	15	7

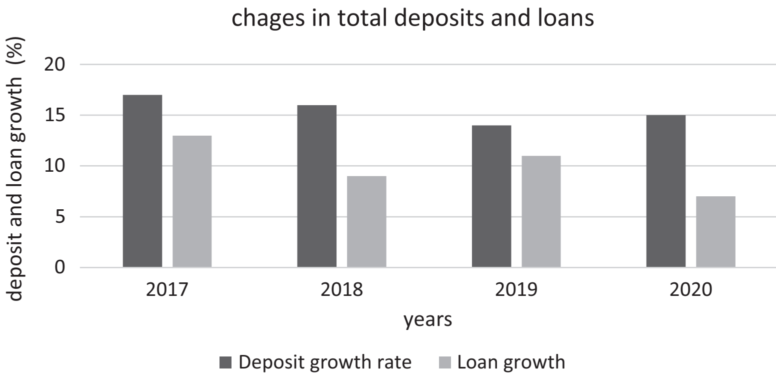

Figure 3.1 Changes in total deposits and loans of bank A in the past four years.

deposit reserves. In the past four years, A The growth rate of bank deposits is greater than the growth rate of loans every year, but the change trend of the growth rate of deposits and the growth rate of loans is basically the same.

4.2 Analyzing the Non-performing Online Loans of Bank A in the Past Four Years, the Non-performing Loan Ratios and the Non-performing Loan Ratio Are Shown in Table 3.2 and Figure 3.2, Respectively

According to Table 3.2 and Figure 3.2, the non-performing loan ratio in 2019 was the lowest point in the past four years, the non-performing loan ratio in 2018 was the lowest point in the past four years, and the non-performing loan ratio gradually increased in 2019 and 2020. Under the influence of macroeconomic policies and the relaxation of capital and loan policies, non-performing loans have increased, and they have remained at around 3.5% in the past two years. But still lower than most commercial banks. It shows that bank A has been more successful in managing credit in recent years.

Table 3.2 Non-performing loan ratios in the past four years

Year	*Non-performing loan ratio (100 million yuan)*
2017	1200
2018	900
2019	700
2020	800

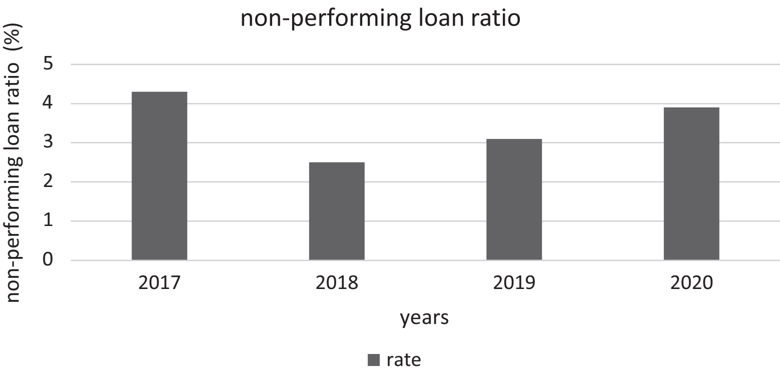

Figure 3.2 Non-performing loan ratio in the past four years.

5 Conclusions

This chapter firstly describes the research background, purpose, and significance, analyzes the current research status at home and abroad, and on this basis, selects bank A as the research object for credit risk management research. Based on the on-site investigation of bank A, the problems in the bank's credit management were analyzed, and corresponding improvement measures and implementation guarantee suggestions were put forward. Combining the actual situation of the bank and the relevant research theories of credit management, this chapter designs the credit risk prevention system, the credit risk internal evaluation and identification system, and the credit risk mitigation system. On the whole, the content of the design basically covers every area of bank A's credit management.

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4 Deep Learning in Detecting Financial Statement Fraud

An Application of Deep Neural Network (DNN)

Santha Muniandy, Nowshath K. Batcha and Geetha A. Rubasundram

1 Financial Statement Fraud

Financial statement fraud (FSF) is a deliberate and intentional omission or misrepresentation of the financial condition of an enterprise (ACFE, 2007; Kim, Baik, and Cho, 2016) and has been a prominent problem for years causing systemic financial meltdowns internationally. Although FSF schemes are the least common amongst the Occupational Fraud components (the other two being corruption and asset misappropriation schemes), it is the most damaging among the three with a median loss of $954,000 (ACFE, 2020). Due to the complexity normally expected from this type of fraud, the typical perpetrator(s) would be from the higher-level management who would normally have the power to override controls or dominate business decisions, and the knowledge to cover up. This explains the high damages and would require strong steps to deter would-be perpetrators from embarking on this path.

Significant steps should be taken to attempt to detect FSF promptly. On average, a typical fraud will last 14 months before detection (ACFE, 2020), which is a long time even with the evolvement of governance and oversight mechanisms that are in place. Whistleblowing has also been a significant cause to detect such misconduct and has been a consistent statistic over the years (ACFE, 2020). In this age of digital growth, more emphasis could be put on technology-based applications to detect FSF. However, it must be remembered that as the digital transformation and controls are growing, the volume of transactions is also increasing, which subsequently leads to the increased complexity of the landscape making tracing FSF more difficult (Ernst and Young, 2019).

FSF can be detected effectively by observing prominent red flags (suspicions of fraud) or other known financial risk indicators (FRIs) that report fictitious revenue, timing differences, concealed liabilities and expenses, improper disclosures, and improper asset valuation (Repousis, 2016). Examples of financial anomalies include increasing revenues that do not correlate with similar growth in cash flow; inconsistent sales growth as compared to others in the industry; rapid and inexplicable rise

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in the number of sales compared to receivables combined with inventory growth and, the large surge in performance during the fiscal year's final period; maintaining consistent gross profit margins while the industry faces pricing pressure; and a large build-up of fixed assets with estimates of an asset's useful life and depreciation that do not correspond to the overall industry.

2 Detecting FSF

Financial ratios analysis, financial statement (FS) analysis, Beneish M-score, and Altman Z-score are among the methods that are widely used to attempt to detect FSF (Skousen, Smith, and Wright, 2009; Glancy and Yadav, 2011; Perols, 2011; Almansour, 2015; Repousis, 2016). Especially, the financial ratios have played a significant role, both independently and as part of other FSF indicator models (Kotsiantis, Koumanakos, and Tzelepis, 2006; Grove and Basilico, 2008; Kanapickienė and Grundienė, 2015) in the attempt to detect FSF.

One such example of the application of financial ratios is the Beneish M-score, which was introduced by Professor Messod Daniel Beneish (Repousis, 2016). The main focus of this M-score was to detect the presence of earnings management (Aris *et al.*, 2015; Aghghaleh, Mohamed and Rahmat, 2016; Repousis, 2016) by using eight main financial ratios as a basis to provide reasonable assurance that FSs are free from material misstatements (Aghghaleh, Mohamed, and Rahmat, 2016). Additionally, Mehta and Bhavani (2017) applied the Beneish M-score as a forensic tool to detect the FSF in Toshiba Corporation.

If the Beneish M-score is greater than −2.22, it indicates a strong likelihood that the firm is manipulating its earnings. Besides the financial ratios and Beneish M-score, horizontal and vertical analyses are also among the other statistical techniques that were used to detect FSF (Aris *et al.*, 2015). Horizontal analysis or also known as trend analysis reports the movements in the key financial elements in the FSs (Pandey, 2020). Vertical analysis analyzes each element in the financial report with a base figure of 100% (Leonov *et al.*, 2020). The combination of financial ratios with vertical and horizontal analyses (FRIs) does add more value to the FSF detection process.

Considering the digital transformation impacts on the businesses and the growing information needs in the cue of detecting and predicting FSF, technology-advanced tools and techniques are needed to cope with evolving complexity in detecting and predicting the FSF. As to meet this need, a new technology, called deep learning (DL) is introduced in this study. This technology emerged with the existing traditional statistical detection techniques to make the FSF detection and prediction more effective.

3 DL to Detect and Predict FSF

DL was introduced by Alexey Ivakhnenko and V.G. Lapa in 1965 (Manovich, 2018). DL is a subset of machine learning (ML), and ML is a subset of artificial intelligence (AI). AI is a technique that enables machines to mimic human behavior, while ML is a technique to achieve AI through algorithms trained with data.

DL is composed of a feedforward multilayer perceptron (MLP), with the ability to learn the representations of data with multiple levels of abstraction (O'Shea and Hoydis, 2017). DL is built on the multiple hidden layers with deep architecture (Jia *et al.*, 2016), and it is a concept that was modeled after the human brain's thought process, also known as 'Threshold Logic'. The hidden layers conduct a non-linear transformation from one layer to the next layer (Schmidhuber, 2015) during the representation learning process. The information passes through several hidden layers, with each output from one hidden layer being the input for the next hidden layer. The first layer in the deep neural network (DNN) is called the 'input layer', and the last layer is called the 'output layer' (Sánchez-DelaCruz and Lara-Alabazares, 2020). All the other layers between these two layers are referred to as 'hidden layers' (Paluszek *et al.*, 2020).

During the representation learning process, the DNN develops abstractions using a combination of mathematics and algorithms to make sense of data such as images, sound, and text (Schmidhuber, 2015; Chen *et al.*, 2018; Marr, 2018). DNN can represent functions with higher complexity when the number of layers and units in a single layer are increased (Liu *et al.*, 2017). The deep architectures allow the DNN to adaptively capture representative information from raw data through multiple non-linear transformations and approximate complex non-linear functions with small error (Jia *et al.*, 2016). The DNN produces specific results for the data by modifying the weight matrix and the bias value at each layer (Tamura and Tateishi, 1997; Siddique and Adeli, 2013; Renstrom, 2018).

In comparison to traditional ML, the DNN outperforms the ML with its ability to process both structured and unstructured inputs meticulously and with high accuracy (Feng *et al.*, 2019). DNN architecture has various quality characteristics and can effectively process a vast and wide range of datasets (Jing and Tian, 2020), both with and without learning supervision. Unlike ML, the DNN does not require an in-depth understanding of the features to best represent the anomalies in the given datasets, as the DNN has a self-learning ability (Aumeister, Runton, and Utz, 2018). This unique self-learning ability allows the DNN to perform the auto representation learning process without supervision and saves the DNN user's time and effort in identifying the best features in the datasets for the best representation learning process. DNN architecture performance primarily depends on the nature and quality of input data. Thus, good quality input is recommended for the best representation of learning results. DNN has the ability to learn and represent the intricate structure in large data sets by using the 'Backpropagation' algorithm (Lecun, Bengio, and Hinton, 2015). This allows the DNN to change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer (Sears, Tandias, and Arroyo, 2018).

There are three types of learning algorithms namely 'supervised learning', 'unsupervised learning', and 'semi-supervised learning' (Shrestha, 2019). The 'supervised learning' algorithms use labeled data to predict patterns and are commonly applied to solve regression problems and make predictions (Domingues, 2015). Meanwhile, the 'unsupervised learning' algorithms are widely applied to identify patterns or structures from unlabeled data using clustering and association methods based on similarities or differences that exist in the dataset (Domingues, 2015). Finally, the 'semi-supervised learning' algorithms are used to handle both labeled and unlabeled data and they can perform classification, regression analysis, clustering, and association.

The DNN's self-learning ability and quality features give a strong heads-up to consider DNNs as an application to detect and predict FSF and its opposite, non-FSF (NFSF) by emerging it with the traditional statistical FSF detection techniques as the base of FSF evaluation. Although there are studies previously done in the context of AI and ML in detecting and predicting FSF, there are very limited studies done in the aforementioned context involving DL and DNN.

The previous studies on DL have focused mainly on the banking and financial sectors. Rönnqvist and Sarlin (2017) introduced a supervised DL model to automate the process to detect the occurrence of significant events in the financial systems to identify financial risk resonating with banking distress and government interventions based on external news sources. Ładyżyński, Żbikowski, and Gawrysiak (2019) applied DL to identify the significant patterns from customer's historical transfer and transactional data, to predict the credit purchase likelihood. Addo, Guegan, and Hassani (2018) introduced DL-based credit risk analysis, to identify the loan receiving capability. Kim (2016) presented a deep convolutional neural network (DCNN) to predict customer's suitability for bank telemarketing. It has been proved that DL can detect fraud on credit card transactions which contributed to reducing losses and fraud prevention for financial institutions.

4 Building the DL and Deep Neural Network Model

This study drives the intention to test the application of DNN as a tech tool to detect and predict FSF and NFSF and to test the accuracy of this new DNN model in meeting the aforementioned intention as illustrated in

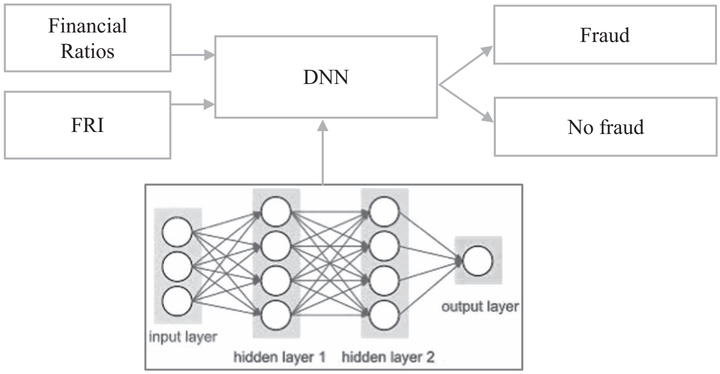

Figure 4.1 Research framework.

Figure 4.1. Financial ratios and FRIs are applied as the basis to detect and predict the FSF and NFSF.

The study samples are selected from public listed companies (PLCs), listed in the United States (US) stock exchanges (NASDAQ and NYSE). The US was selected as the focal geography area for this study because it was listed as the top region with 886 fraud cases under the 2020 Report to the Nations (ACFE, 2020). Also, the PLCs are selected for sampling instead of privately held companies because of (1) data availability – the PLCs' annual reports are readily available on the company's websites and various other easily accessible internet sources and databases; (2) similar accounting standards – the PLCs adopt the same set of generally accepted accounting principles (GAAP); (3) similar reporting framework and structure – the PLCs adopt the same reporting framework and structure; (4) similar reporting currency – the PLCs report their FSs in USD; and finally, (5) sharing the same PESTEL (Political, Economic, Social, Technology, Environmental, and Legal) impact – the PLCs go through the same set of PESTEL impacts (both positive and negative) in the given time frame.

The PLCs were selected from five different industries that were identified as high fraud risk industries in the 'ACFE 2020 Report to the Nations', with a high number of fraudulent case records. The selected five industries are inclusive of healthcare (with 147 fraud cases), energy (with 91 fraud cases), manufacturing (with 181 fraud cases), technology (with 65 fraud cases), and services (with 29 fraud cases). In this study, each selected industry is represented by five companies (in total 25 companies) that fall within the capitalization bracket of $8.7 million to $1.6 trillion. These 25 companies were further categorized into (1) companies with FSF history and (2) companies without FSF history. The ratio of the companies with and without FSF history is 20%:80%. Further, the name of the companies without FSF history

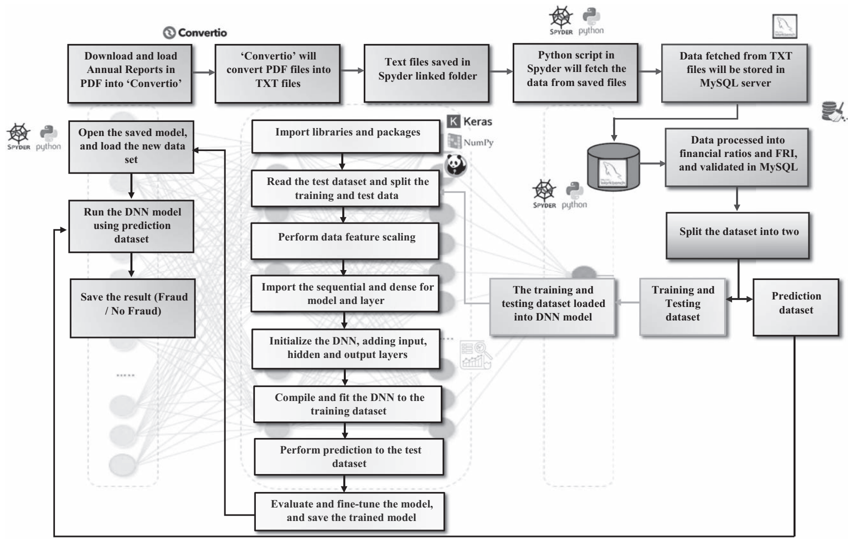

Figure 4.2 DNN model data flow.

have been kept anonymous to conceal the sensitivity of the FSF prediction. The dataset for this study was extracted from published annual FSs (10-K reports) for 19 consecutive years from the year 2000 up to 2018. In total, 475 annual reports were processed as input datasets for the DNN model.

The entire DNN model is sub-divided into five main processes and the process flow is shown in Figure 4.2. The main five processes include (1) data preparation, (2) data pre-processing, analysis and validation, (3) data preparation for DNN testing, training, and evaluation, (4) DNN model setup, configuration, training, testing, and performance evaluation, and finally, (5) use the trained DNN model for FSF and NFSF detection and prediction.

4.1 DNN Model Process Flow

The DNN model's 'data preparation process' starts with downloading the annual reports in PDF format. Then, these annual reports are converted into text files using 'Convertio' (an online PDF converter) and saved in a folder using unique file references that are linked to the 'Spyder' programming platform. A 'Python' script is specifically programmed to read the text files that were saved in the folder and to fetch the key financial elements' values (listed in Table 4.1). The programming script reads the FSs in the annual report which covers the statement of profit or loss, the statement of financial position, and the statement of cash flow. Also, this programming script is designed to fetch data for 19 years (from 2000 to 2018) per company per run.

Table 4.1 Key financial elements from the annual report

Financial statement	*Key financial elements (MySQL data ID)*
Statement of profit or loss	Total revenues (REVENUE)
	Direct expenses or cost of goods sold (DE)
	Gross profit (GP)
	Interest and debt expense (INTEREST)
	Earnings before income taxes (EBIT)
	Income tax expenses (TAX)
	Net earnings (NP)
	Basic earnings per share (EPS)
Statement of financial position	Cash and cash equivalents (CCE)
	Accounts receivable (AR)
	Inventories (INVENTORY)
	Total current assets (TCA)
	Property, plant and equipment, net (PPE)
	Total non-current assets (TNCA)
	Total assets (TA)
	Total current liabilities (TCL)
	Total non-current liabilities (TNCL)
	Total current liabilities (TL)
	Retained earnings or deficit (RE)
	Accumulated other comprehensive income or loss (AOCL)
	Total shareholders' equity (TSE)
	Total equity (TE)
	Total liabilities and equity (TLE)
Statement of cash flows	Depreciation and amortization (DEPRECIATION)
	Net cash provided/(used) by operating activities (CFOA)
	Net cash provided/(used) by investing activities (CFFA)
	Net cash provided/(used) by financing activities (CFIA)

Source: Author's own.

Those key financial elements' values fetched from annual reports will automatically be stored in the MySQL database under the 'financial' table. Figure 4.3 shows the sample 'financial' table view in MySQL Workbench.

The next stage of DNN's model process flow covers the 'data pre-processing, analysis, and validation'. In this stage, the raw data fetched from text files will be massaged, validated, analyzed, and processed into financial ratios and FRIs in MySQL Workbench.

The data in the 'financial' table is further processed into several stages and managed under different tables for each processing stage within the MySQL database. Figure 4.4 shows the list of MYSQL data tables used in the data processing stage.

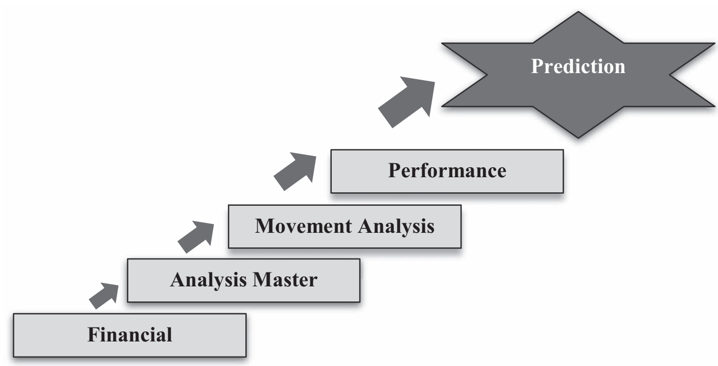

Figure 4.3 MySQL data tables list.

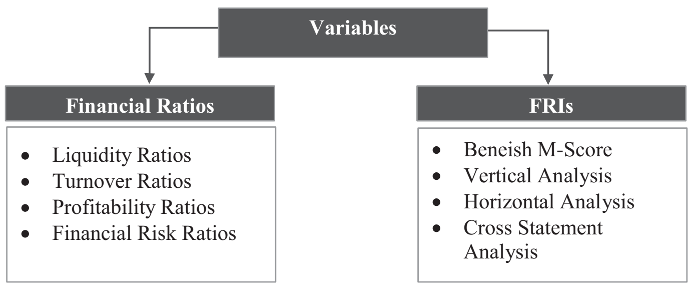

Figure 4.4 Main variables (financial ratios and FRIs).

4.1.1 Data Analysis

From the 'financial' table, the data are further processed into financial ratios and FRIs, and the outcome is saved in the 'analysis master' table. The financial ratios and FRI are the main variables applied in this study as a basis to detect and predict the FSF and NFSF. The key financial ratios and FRIs that are applied as variables in this study are listed in Figure 4.5. Using the vertical, horizontal, and cross statement analysis, 15 key FRIs were identified as listed in Table 4.2. These key FRIs are applied as the basis to indicate possible earnings manipulations in the FS.

The key elements from FS together with the outcome from financial ratios and FRI computations are now applied to perform movement analysis. The results from movement analysis are stored under the 'movement analysis' table. The below-attached formula is used to compute the movements in each element listed under the 'analysis master' table.

Movement in X = current year × balance – immediate prior year × balance

Table 4.2 Financial risk indicator (FRI) list

FRI	Formula and details
FRI 1	Total non-current assets (TNCA) movement/revenue movement
This indicator relates the TNCA movements to Revenue movements. A positive movement in this indicator denotes growth in economic contribution from total assets, while a negative movement denotes asset underutilization.	
FRI 2	Working capital/revenue
This indicator relates the working capital to revenue. A positive movement indicates an increase in the company's liquidity.	
FRI 3	Property, plant, and equipment (PPE)/total assets
This indicator relates the PPE to total assets. A negative movement will indicate that the company's investment in PPE has reduced and this might affect the long-term profitability of the company (Guan, Kaminski and Wetzel, 2007).	
FRI 4	Cash and cash equivalent (CCE)/total current assets
This indicator relates the CCE to total current assets. A positive movement shows an increase in CCE over the years and this shows the company is maintaining enough cash and shows an increase in liquidity capacity of the company.	
FRI 5	Accounts receivable (AR) movement/total assets
This indicator relates the AR movements to total assets. A positive movement shows an inefficient debt collection. This might lead to an increase in bad debt and affect the net profit of the year. This could also indicate possible fictitious revenue recognition (Guan, Kaminski and Wetzel, 2007).	
FRI 6	Cash from investing activities (CFIA) movement/total non-current assets (TNCA) movement
This indicator relates the CFIA movements to TNCA movements. A positive movement denotes that the investments in tangible and intangible assets are reduced. This might have an impact on the company's sustainability in the upcoming future.	
FRI 7	Property, plant, and equipment (PPE) movement/cash from operating activity (CFOA)
This indicator relates the PPE movements to CFOA. A negative movement denotes a reduction in PPE and subsequently affects the economic benefits/cash inflows. The reduced economic benefits might impact the CFOA negatively. A positive movement is deemed favorable for this FRI.	
FRI 8	Account receivable (AR) movement/cash from operating activity (CFOA)
This indicator relates the AR movements to CFOA. A positive movement denotes an increase in AR and will negatively affect the CFOA which reflects reduced cash inflows. This could also indicate possible fictitious revenue recognition.	
FRI 9	Total current liability (TCL) movement/cash from operating activity (CFOA)
This indicator relates the TCL movements to CFOA. A positive movement denotes an increase in cash reserve and well-planned credit terms, in which the payment cycle is longer than the collection cycle.	
FRI 10	Cash from financing activity (CFFA) movement/total non-current liability (TNCL)
This indicator relates the CFFA movements to TNCL. A negative movement indicates a reduction in liability as the company is settling its long-term loans. A positive movement indicates an increase in new loans and subsequently leads to an increase in the company's leverage level.	

(*Continued*)

Table 4.2 (Continued)

FRI 11	Inventory movements/revenue movement
This indicator relates the inventory movements to revenue movements. A negative movement indicates an increase in sales and improvement in inventory and production management (Guan, Kaminski and Wetzel, 2007).	
FRI 12	Tax/earnings before interest and tax (EBIT)
This indicator relates the tax to EBIT. A positive movement indicates that the organization has enough profit to pay its tax obligations.	
FRI 13	Administrative expenses movement/total current liabilities (TCL)
This indicator relates the administrative expenses movement to TCL. A positive movement indicates that the organization needs to pay attention to increasing fixed costs and should take necessary action to reduce non-operational related costs.	
FRI 14	Depreciation movement/PPE movement
This indicator relates to the depreciation movement and PPE. A positive movement indicates that the new PPE has increased the depreciation expenses. A negative movement might indicate possible changes in the estimation of an asset's useful life or changes in depreciation policies during the year which could be an indicator of profit or cost manipulation.	
FRI 15	Interest/CCE
This indicator relates to Interest and TCA. A positive movement indicates growth in an organization's capacity to pay the interest obligation.	

Source: Author's own.

Once the movement analysis data are populated into the 'movement analysis' table, these data will further be processed to compute the performance for each element. The performance analysis results will be stored in the 'performance' table in the MySQL database. Below shown the formula used to compute the performance.

Performance of X = movement in X/immediate prior year × balance

The next step in this stage is the data validation process, where key checkpoints (CPs) are applied to identify NFSF (Table 4.3 shows the CP list). A data validation script is programmed in MySQL to analyze the dataset and anyone sample (one-year dataset) that fails the CP requirements will be identified as FSF. This programming script excludes data from the year 2000 and only validates those data from the years 2001 to 2018. This is because for the year 2000 there are no comparative figures available (no data available for the year 1999) to perform any sort of performance movement analysis. The final output from the validation process was used as datasets for DNN model testing and training, the final prediction, and the DNN's results' evaluation. This supervised validation method is referred to as the prediction and detection of FSF and NFSF using the formula (FOR). The final outputs are stored in the MySQL database.

The next process will drive the DNN's model process flow into the third stage, the data preparation for DNN testing, training, and evaluation. Once all 450 samples (18 years × 25 companies = 450) were validated in MySQL,

Table 4.3 Data validation checkpoints (CP)

Check points	*NFSF validation test*
CP#1	Current ratio > 1; quick ratio > 1; cash ratio > 1
CP#2	Current ratio performance > 0; quick ratio performance > 0
CP#3	Receivable turnover ratio performance > 0; capital turnover ratio performance > 0; asset turnover ratio performance > 0
CP#4	Net profit margin performance > 0; return on investments performance > 0; gross profit margin perf > 0; operating profit margin performance > 0; return on assets performance > 0; return on equity > 0
CP#5	Debt to equity < 1; debt to asset < 1; debt to equity performance < 0; debt to asset performance < 0; interest cover ratio performance > 0; ROCE performance > 0; return on net worth performance > 0
CP#6	FRI 1 performance > 0; FRI 2 performance > 0; FRI 3 performance > 0; FRI 4 performance > 0; FRI 5 performance < 0; FRI 6 performance < 0; FRI 7 performance > 0; FRI 8 performance < 0; FRI 9 performance > 0; FRI 10 performance < 0; FRI 11 performance < 0; FRI 12 performance > 0; FRI 13 performance < 0; FRI 14 performance > 0; FRI 15 performance > 0
CP#7	Beneish_M_Score < -2.22

Source: Author's own.

the dataset was then divided into two: (1) one set for DNN testing and training and (2) one set for DNN final prediction and detection process. Both datasets are stored in the 'Keras Engine' linked folder.

The next stage is the most vital process in the DNN model's process flow. This stage covers the DNN model setup, configuration, training, testing, and performance evaluation. The whole process is managed in the Spyder platform. The first step in the DNN model setup is to import 'Keras', 'Numpy', 'Matplotlib', and 'Pandas' libraries and packages into the Spyder platform.

The next process initiates the model configuration, where the programmed scripts are applied as the DNN model's parameter. The parameter setups' details are as follows. Using the train_test_split function from the sci-kit-learn's model selection module, the script will retrieve the testing and training dataset from the 'Keras Engine' linked folder and randomly split the training and test dataset into two: (1) training dataset and (2) testing dataset. In this study, the train_test_split was set at 70:30. This means 70% of the dataset is used for training while the remaining 30% will be used for model testing. The random seed (random_state=1) function was set to shuffle the training and testing dataset internally before splitting to ensure the results are reproducible.

The StandardScaler class was loaded from the pre-processing module and initialized to estimate the parameters, μ (sample mean) and σ

(standard deviation), for each feature dimension from the training and testing dataset. The transform method was applied to standardize the training and testing dataset based on the estimated parameters, μ and σ. The same scaling parameters were used to standardize the training and testing dataset so that both values in the training and testing dataset (after the split) are comparable.

The Sequential module was imported from Keras to add the training and inference features. The Sequential module is suitable for a plain stack of layers where each layer has exactly one input and output tensor. This module is not suitable when the model has multiple inputs or multiple outputs when there is a need for layer sharing or a need for non-linear topology (for example, a residual connection, a multi-branch model).

The Keras.layers module is also used to build blocks of neural networks (NN) in Keras. A layer consists of both tensor-in and tensor-out computation functions (the layer's call method). The dense function also is imported from the Keras-layers and these layers come after the input layer to learn the weight matrix. The first dimension of the matrix is the input data, and the second dimension is the output data. The Sequential class was created using the Keras. This Sequential function is used to create the DNN (first layer) and add the DNN (hidden layers) to the DNN model.

A classified supervised learning algorithm was used to predict the categorical labels (1 – FSF or 0 – NFSF). The kernel_initializer was used to initialize the weights for NN. The NN needs to start with weights and then iteratively upgrades them to better values. In the case of statistical distribution, the library will generate numbers from that statistical distribution and use them as starting weights. For this model, the uniform distribution was used to initialize weights.

The Rectified Linear Unit (ReLU) activation function is used in this DNN model. This function returns '0' if it receives any negative input and helps to keep the output layer more specific and cleaner. Also, when the additional layers are created in the model, the ReLU will be repeated with variations.

Additionally, the sigmoid function is also applied to represent the *X*-axis as the input and the *Y*-axis refers to the output. When the value in the input axis increases (*X*-axis), the value in the output axis (*Y*-axis) will reduce. Eventually, no matter how much data was used, the highest value will be +1.0 and the lowest will be −1.0. This ensures that the neuron's value is within the range of $-1.0 < f(x) < 1.0$ and this helps to keep the neural network bounded and stable.

For this study, the DNN architecture is set to consist of one input layer, two hidden layers, and one output layer. The training observation number is set into the input layer together with the number of neurons in the first layer. Subsequently, the DNN representation learning process was started to take place in the hidden layers (using the output from the input layer). At the end of the representation learning process, the output layer (final layer) provided one status per sample (either with FSF or NFSF) as the outcome as this output layer is set for only one neuron. Figure 4.5 shows the DNN architecture for FSF and NFSF detection and prediction.

For the model compilation, the optimizer is set for 'adam'. Adam is an optimization algorithm that is used to update network weights iterative based on the training dataset instead of the classical stochastic gradient descent procedure. Also, the loss function was added to compute the quantity that the DNN model should seek to minimize loss during the training and to compute the cross-entropy loss between true labels and predicted labels. For this model, binary_crossentropy is applied because there are only two labels of classes (0 – NFSF and 1 – FSF). The metrics are set to accuracy and used to judge the performance of the model. It is like a loss function, except that the results from evaluating a metric are not used when training the model. The accuracy metric helps to compute the accuracy rate across all predictions.

Finally, to ensure the DNN fits the training dataset, the number of epochs is set at 100, and the batch size is set at 32. This builds an indefinitely repeating dataset, which will be passed to the fit () method to train the model. This will enable the fit () method to keep track of the epochs, it needs to know the number of steps for each epoch. The verbose set for 1 (verbose=1) shows the training progress for each epoch.

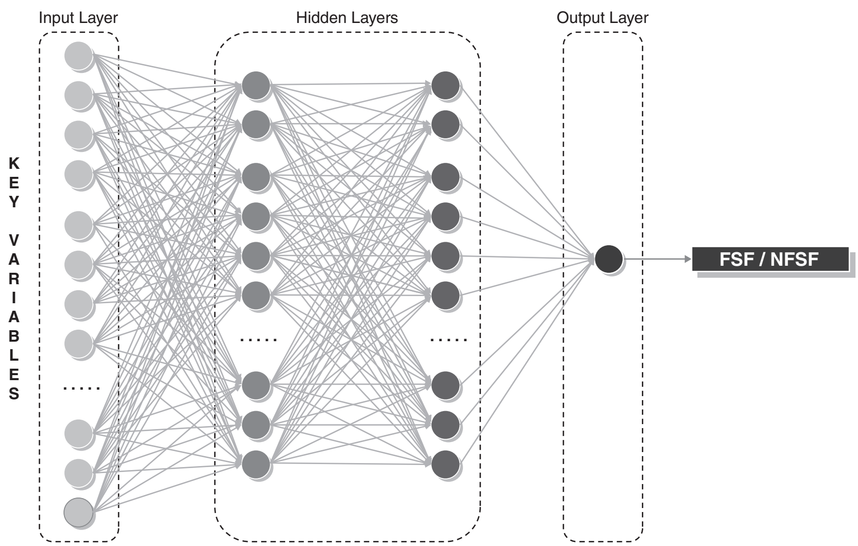

Figure 4.5 DNN architecture for FSF and NFSF detection and prediction.

Following the model training configuration, the predict function is used to test detection and prediction outcomes for the test dataset. This model is set to classify the score above 0.5 as 'FSF' and the score below 0.5 as 'NFSF'.

The final stage in the DNN model's process flow covers the methods applied to use a trained DNN model for FSF and NFSF detection and prediction. The Confusion Matrix was applied to review the performance of the DNN model in predicting FSF and NFSF using the test dataset. The Confusion Matrix was used to visualize the prediction performance as this study has adopted a classification model (Sundararaj, 2017). The accuracy of prediction is represented in the percentage of cases correctly classified and the accuracy formula for the binary classifier is as follows (Patro and Ranjan Patra, 2014).

Accuracy % = (TP + TN)/(TP + TN+ FP + FN), where

'True positive' (TP) is the case with no fraud which has been correctly classified as NFSF by DNN.
'True negative' (TN) is the case with fraud which has been correctly classified as FSF by DNN.
'False positive' (FP) is the case with fraud that has been incorrectly classified as NFSF by DNN.
'False negative' (FN) is the case with no fraud which has been incorrectly classified as FSF by DNN.

The DNN model's accuracy score on successful predictions of the FSF and NFSF using the test dataset is concluded at 88.99% [100% − 11.11% (6/54 × 100)]. The lack of inaccuracy by 11.11% is due to six samples that fell under the 'FP' category. Table 4.4 shows a summary of the confusion matrix results for the test dataset.

Table 4.4 shows that the model has tested 54 samples in total and has classified 47 samples as 'TP' (with NFSF), 1 sample as 'TN' (with FSF), and 6 samples as 'FP'. 'FP' is interpreted as 6 samples containing 'fraud' indicators; however, the model failed to capture these samples as FSF, instead, the model has classified these samples as NFSF. A high prediction accuracy

Table 4.4 Confusion matrix results for the testing dataset

		Predicted	
		Fraud	
Actual	No fraud	True positive 47	False negative 0
	Fraud	False positive 6	True negative 1

Source: Author's own.

showed that the DNN model is ready for use and the trained DNN model is now ready to be used to detect and predict the FSF and NFSF in the prediction dataset

5 Results and Discussion

The final prediction results using the prediction dataset are presented in the confusion matrix table as per Table 4.5.

The FSF and NFSF detection and prediction results accuracy (ACC) shows 89.11% [(376 (TP) + 25(TN))/450] and the error rate (ERR) is 10.89% [(48 (FP) + 1(FN))/450], which is due from FP and FN collectively. This prediction result matches the DNN's model accuracy using the test dataset. The accuracy results prove that the DNN can detect and predict the FSF and NFSF accurately using supervised DL.

To further elaborate on the results, a comparison of companies with FSF and NFSF is presented in the confusion matrix in Tables 4.6 and 4.7.

Referring to confusion matrix, the overall detection accuracy (ACC) rate is 88.89% [(75 (TP) + 5 (TN))/90] and ERR is 11.11% [(9 (FP) + 1(FN))/90].

In total, there are 75 samples with the NFSF situation and 5 samples with the FSF situation. There are nine samples (FP) detected as NFSF; however,

Table 4.5 Confusion matrix table (final results)

		Predicted	
		Fraud	
Actual	No fraud	True positive (TP) 376	False negative (FN) 1
	Fraud	False positive (FP) 48	True negative (TN) 25

Source: Author's own.

Table 4.6 Confusion matrix (companies with FSF history)

		Detected	
		Fraud	
Actual	No fraud	True positive (TP) 75	False negative (FN) 1
	Fraud	False positive (FP) 9	True negative (TN) 5

Source: Author's own.

Table 4.7 Confusion matrix (companies without FSF history)

		Predicted	
		Fraud	
Actual	No fraud	True positive (TP) 301	False negative (FN) 0
	Fraud	False positive (FP) 39	True negative (TN) 20

Source: Author's own.

according to FOR results, these nine samples are detected to have FSF. Similarly, one sample (FN) was detected as FSF, instead of NFSF. The accuracy results prove that the DNN can detect the FSF and NFSF accurately for companies with FSF history using supervised DL.

In total, 360 samples were tested under the category of companies without FSF history. The results show that the DNN has correctly predicted 301 samples with the NFSF situation and 20 samples with the FSF situation. Meanwhile, DNN missed predicting 39 samples with the FSF situation, instead, it classified those samples wrongly as NFSF. Referring to Confusion Matrix, the overall prediction accuracy (ACC) rate is 89.17% [(301 (TP)+ 20 (TN))/360] and ERR is 10.83% [(39 (FP) + 0(FN))/360]. The accuracy results prove that the DNN can predict the FSF and NFSF accurately for companies without FSF history using supervised DL.

Further, Table 4.8 provides a comparison of the prediction rate by industries as well as the difference between FSF and NFSF. Though seemingly still accurate, there are differences caused by industry factors. This reflects that an industry-specific focus would possibly create a more accurate prediction rate by ensuring more relevant variables are taken into consideration.

To summarize the result analysis, Table 4.9 shows the confusion matrix evaluation of the overall performance of this DNN model with comparison

Table 4.8 Industry based result analysis

Industry	*Average anomalies detection (%) with FSF history*	*Average anomalies prediction (%) with no FSF history*
Healthcare	100	88.89
Diversified machinery	88.89	83.20
Oil and gas	83.33	94.44
Computer peripherals	83.33	93.05
Aerospace and defence	88.89	87.50

Source: Author's own.

Table 4.9 Confusion matrix evaluation

Confusion matrix measures	*Description*	*Overall*	*With FSF history*	*Without FSF history*
Error rate (ERR)	**(FN + FP)/total dataset** ERR was calculated as all incorrect detections and predictions divided by total samples. The best ERR is 0.00, and the worse ERR is 1.0.	0.11	0.11	0.11
Accuracy (ACC)	**(TP + TN)/total dataset** ACC is calculated using the right predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. It can also be calculated by 1 – ERR	0.89	0.89	0.89
Sensitivity (SN)	**TP/(TP + FN)** SN is calculated by dividing the true positive with the total number of correct predictions (including both TP and FN). It is also referred to as recall (REC) or True Positive Rate (TPR). The best sensitivity is 1.0, whereas the worst is 0.0.	1.00	0.99	1.00
Specificity (SP)	**TN/(TN +FN)** SP is calculated as the number of correct negative predictions divided by the total number of negatives. It is also called a true negative rate (TNR). The best specificity is 1.0, whereas the worst is 0.0.	0.96	0.83	1.00
Precision (PREC)	**TP/(TP + FP)** Precision (PREC) is computed by dividing True Positive with total positive predictions. It is referred to as positive predictive value (PPV). The best precision is 1.0, whereas the worst is 0.0.	0.89	0.89	0.89
False positive rate (FPR)	**1 – specificity** FPR is calculated by 1 minus specificity value. The best false positive rate is 0.0 whereas the worst is 1.0.	0.04	0.17	0.00

(*Continued*)

Confusion matrix measures	*Description*	*Overall*	*With FSF history*	*Without FSF history*
Prevalence	**(TP + FP)/(TP + FP + FN + TN)** This measures the frequency of positive predictions	0.94	0.93	0.94
Matthews correlation coefficient (MCC)	**TP × TN − FP × FN/(√(TP + FP) (TP + FN) (TN + FP) (TN + FN)** MCC is a correlation coefficient calculated using all four values in the confusion matrix.	0.54	0.5	0.55
Negative Predictive Value (NPV)	**(Specificity × (1 − prevalence))/(((1 − sensitivity) × prevalence) + ((specificity) × (1 − prevalence)))** NPV is defined as the proportion of predicted negatives that are real negatives. It reflects the probability that a predicted negative is a true negative.	0.96	0.82	1.00
Balanced Accuracy	**(Sensitivity + specificity)/2** Similar to accuracy, this measure is used to describe the classification performance of the model	0.98	0.91	1.00
F1 score	**F1 = 2TP/(2TP + FP + FN)** This measures the weighted average of Precision and Recall	0.94	0.94	0.94

Source: Author's own.

to both with FSF history and without FSF history. The sensitivity, specificity, and precision show a score near or equal to 1.0. Similarly, the prevalence, negative predictive value, balanced accuracy, and F1 scores show a score near or equal to 1.0. The Matthews correlation coefficient showed a score of above 50% and the FP rate reported close to or equal to 0. All the aforestated results reflect the accuracy and reliability of the model.

6 Conclusion

The DNN model developed in this study can accurately predict and detect FSF and NFSF using the supervised DL with an accuracy rate of 89.91%, which is above the average of other NN-based learning algorithms (which is at 86.91%). The DNN model results are relatively close to the study conducted by Kotsiantis, Koumanakos, and Tzelepis (2006) which reported accuracy results of over 90% using stacking, voting, BestCV, grading, and stacking ML algorithm. Similarly, this DNN model is also at par with the decision tree model applied by Mehta and Bhavani (2017). This model also outperforms the fuzzy neural network (FNN) introduced by Lin, Hwang, and Becker (1997) with an improved accuracy variance of 13.11%. It must be remembered that this is a pioneer study and the sample size and further considerations to be improved to ensure that this model's self-learning ability develops and improves the prediction and detection accuracy level.

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5 Predicting Stock Return Risk and Volatility Using Neural Network

The Case of the Egyptian Stock Exchange

Maha Metawea, Saad Metawa and Noura Metawa

1 Introduction

Predicting stock return volatility with traditional statistical methods has proven to be a difficult task. An artificial neural network (ANN) may be more suitable primarily because no assumption about a suitable mathematical model has to be made prior to forecasting. Furthermore, a neural network model has the ability to extract useful information from large sets of data, which often is required for a satisfying description of a financial prediction.

Increased globalization of the financial market has made stock return volatility an important research topic and challenge for both: practitioners, researchers and policymakers. The most recent liberalization of economic policies and exchange rate regimes in many developing countries including Egypt have caused the realignment of competitive structures of many emerging stock markets and their relative attractiveness to both local and global markets alike. This task will be achieved through the comparison between the degree of accuracy of the proposed ANN model against the accuracy of the alternative model – the generalized autoregressive conditional heteroscedasticity (GARCH) model which has dominated the research area for many years (Almasi Monfared and Enke, 2014). Moreover, the results of this study will provide a set of recommendations that are expected to be helpful to both individual and institutional investors in the Egyptian Stock Market in rationalizing their investment decisions on one hand and to the Egyptian policymakers in their efforts to improve market surveillance and efficiency on the other hand. Qiu and Song (2016) have indicated that it has always been a difficult task to predict the exact daily return of the stock market index; hence, there is a great deal of research being conducted regarding the prediction of the direction of the stock return index movement. Many factors including political events, general economic conditions and traders, expectations have an influence on the stock market index.

The purpose of this study is to predict the dominant factors that affect stock market return volatility. The study will use two types of two competing

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analytical and prediction models: generalized least squares (GLS), GARCH and logit model and an ANN to examine the factors that affect stock market return volatility.

There are several definitions of stock return volatility. According to one of the leading definitions in this area, volatility is defined as a statistical measurement of the changes in returns or market index (Almasi Monfared and Enke, 2014) Volatility can be measured using either the standard deviation or variance between returns from the market index. Typically, a higher degree of volatility is considered more dangerous for stability in the field of finance. Other scholars in the area define volatility as the degree of variation in a series of trading returns over a certain period of time (Chaudhuri and Ghosh 2016). Volatility is commonly measured by the standard deviation of returns where the symbol "σ" is used as a measure of volatility, which should not be confused with the variance of the same name, which instead σ^2 (Table 5.1).

Table 5.1 Study variables

The variable	*Definition*
A Internal factors	
1 Size of the company(represented by the log of total assets)	The final amount of all gross investments, cash and equivalents, receivables and other assets as are presented on the balance sheet.
2 Earning per share	Measured by dividing the net income by the number of shares outstanding.
3 Market-to-book value	A financial valuation metric is used to evaluate a company's current market value relative to its book value.
4 Mean stock return	Measured by the average return for the month.
B External factors	
1 Exchange rate growth	Measured by the value of the Egyptian Pound (LE) in terms of the US Dollar.
2 Inflation rate growth	The percentage change in the value of the wholesale return index (WPI), on a month-to-month basis. It measures the change in returns of goods and services over a specific period.
3 Interest rate growth	A rate that is charged or paid for the use of money. It is expressed as an annual percentage of the principal. It often changes as a result of inflation and Central Bank policies.
4 GDP growth	Gross domestic product (GDP) is the monetary value of all the finished goods and services produced within a country's borders in a specific time period. Measured by the log of the monthly GDP.

2 Literature Review

A large number of empirical studies have been formed to determine the factors affecting stock return volatility. In this section, some of these studies will be reviewed. However, most of these studies have been conducted in the developed countries, but there have been rarely studies that focused on the developing countries, especially Egypt.

Factors affecting stock return volatility have been studied from so many different points of view. A lot of researchers examined the relationships between stock return volatility and selected factors that could be either internal or external.

In our study, we list three factors as internal factors that may affect stock return volatility [company size represented in total assets, earning per share (EPS) and market-to-book value]. The researcher also lists four external factors that may affect stock return volatility (exchange rate, interest rate, inflation rate and the gross domestic product (GDP)].

The study focused on the factors that affect the stock return volatility either company-specific or macroeconomic variables, many researchers have examined these factors from many points of view. According to the literature review, numerous studies have attempted to explain the effect of company-specific factors on stock return volatility. Research conducted by Hartono (2004) examines the effect of a sequence of positive and negative dividend and earning information on stock returns. Results show that the positive recent earning information has a significant relationship with stock returns when it follows negative dividend information, and the negative recent earning information has a significant relation with stock returns when it follows positive dividend information.

Several studies thus far have linked Company-specific factors with stock return volatility, Hashemijoo et al. (2012) study has shown a significant negative relationship between share return volatility with two main measurements of dividend policy which are dividend yield (DY) and dividend payout. Moreover, a significant negative relationship between share return volatility and size is found.

Zakaria et al. (2012) found that only 53.53% of the volatility in the share returns are explained by DY and dividend payout ratio (DPR). DPR significantly influences the volatility in share return. The greater the size of the company, the more significant impacts the volatility of share return would be. DY, investment growth and earnings volatility insignificantly influence the changes in the company's share returns.

A number of authors have reported a significant effect of macroeconomic variables on stock return volatility. Kasman et al. (2011) conducted a study on the effects of interest rate and foreign exchange rate changes on Turkish banks' stock market returns using the GARCH model. The sample consists of 13 Turkish commercial bank stocks listed on the Istanbul Stock Exchange. They used daily closing individual Bank stock returns, the closing return of the bank index, exchange rates and interest rates. The period begins on 27 July 1999 and ends on 9 April 2009. The results have indicated that there's a negative and significant effect of interest rate and exchange rate changes on the conditional bank stock return. Also, Vikalp et al. (2018) conducted a detailed analysis of the different relations between the prediction and individual stock returns of financial sector companies on the National Stock Exchange and a set of macroeconomic variables as independent variables. The result has shown that macroeconomic variables and physical factors will affect the share returns of the different stock returns. Because of the strong relationship between the macroeconomic variables and different stock values it plays a vital role.

Erdem et al. (2005) also studied the effect of macroeconomic variables on the Turkish stock exchange returns. The list of the independent variables used in the study included: exchange rate, interest rate, inflation, industrial production and money supply. A GARCH model was used in the study to test the effect of macroeconomic variables on stock return volatility. Results reveal a unidirectional strong effect of inflation and interest rate on all stock return indexes. There is a strong effect of money supply on a financial index, and from exchange rate to both IMKB 100 and industrial indexes. There is no effect of industrial production on any index.

On the other hand, many studies also have examined the use of ANN in the prediction of stock return volatility. Chaudhuri and Ghosh (2016) conducted a comprehensive study on the use of neural network models in the prediction of stock return volatility in the Indian stock market. In this study, the researchers used a backpropagation algorithm type of neural network to make the prediction of the stock market volatility more accurate. The study model was based on the Indian VIX, CBOE VIX indices and the volatility of crude oil returns (CRUDESDR), volatility of DJIA returns (DJIASDR), volatility of DAX returns (DAXSDR), volatility of Hang Seng Index returns (HANGSDR) and volatility of Nikkei returns (NIKKEISDR) as predictor variables. The study shows that only one hidden layer was used while the number of hidden neurons has been varied at three levels (20, 30 and 50, respectively). Hence, the total number of trials was 54 ($2 \times 9 \times 3$). The time frame for this study has tested three different time periods. The framework of the study could satisfactorily forecast volatility for 2015 using training data for 2013–2015.

Agrawal and Murarka (2015) study examined the stock return trend prediction using ANN and derived parameters. The researchers indicated that the use of neural networks in the field of finance has significantly increased over the last two decades. Furthermore, different types of neural network models have been used in predicting stock returns and return fluctuations. The success of those models has the potential to bring numerous rewards – both academic and financial analysts. There are numerous reasons why neural networks offer an advantage in the quest to predict stock return fluctuations. There is only one widely accepted theory on stock returns and markets, called the efficient markets hypothesis (EMH), which ultimately concludes that such return changes may never be predicted.

3 Methodology (Figure 5.1)

3.1 The Sample

The largest, most actively trading companies representing the most popular Egyptian Stock Exchange indices – EGEX 30 – were included in the final sample of this study. The combined market value of these companies is more than 50% of the total value of all listed companies.

3.2 Data Collection

1 The entire data set related to the internal variables used in the study was obtained from the Department of Economic Research of the Egyptian Stock Exchange. The Quarterly and Annual Financial reports for all listed companies – for the 2014–2017 periods – were extracted from the data set. Those companies include: the 30 companies of the Egyptian Stock Exchange Index (EGEX 30) in addition to 10 other actively traded companies. After a detailed examination of the data set, the Quarterly and Annual Financial reports for 40 companies were selected for inclusion in the study sample. The final selection was made on the basis of data availability and consistency for the whole study period.

2 The values of the company-specific variables [log-TA, EPS, price-to-book value (P/BV) and the average monthly return used in the study] were calculated.

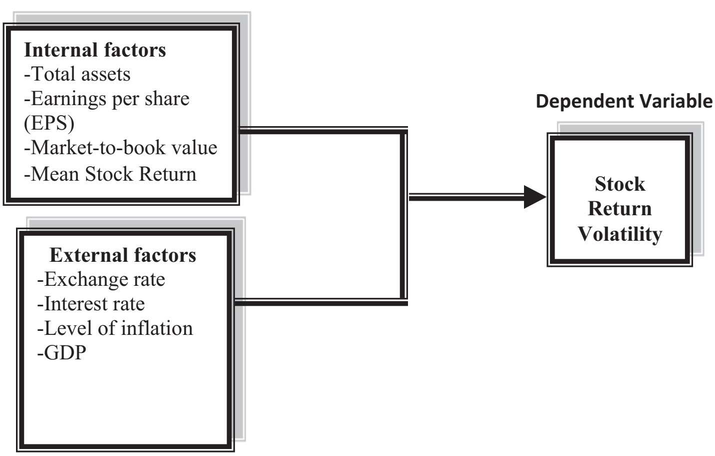

Figure 5.1 The study model.

3 Nine companies were excluded from the final sample due to the presence of some irregularities in the financial reports of those companies and the incompleteness of required data.
4 Data for macro variables (exchange rate, interest rate, inflation rate and GDP) were gathered from the monthly *Economic Bulletins* published by the Egyptian Central Bank over the study period.
5 Data were reviewed and compiled using Excel Sheets in which the study data set was arranged as columns containing: company name along with computed values of the study variables. Only two variables, total assets and gross national product, were transformed to the log form due to their special nature – values made of several digits – in order to make them consistent with the values of other variables used in the study.
6 As a normal practice in this type of studies, the data were preprocessed where extreme (outliers) were eliminated.

3.3 Framework for Data Analysis

As this study involves the use of three different models, the GLS model, GARCH model and ANN model, the standard descriptive analysis is used to describe the main characteristics of data used – including mean, median, range, variance and standard deviations. In addition, correlation matrices measuring the relationships among the study variables were also computed.

3.4 Study Time Frames

Two time frames were used in the study: yearly analysis and full period analysis. Since the study period (2014–2017) has witnessed various types of economic and political changes including the implementation of the economic recovery program, the liberalization of the exchange rate regime and the unprecedented increase in interest rates in 2016, the first type of analysis (yearly analysis) was designed to gain more insights into the phenomenon under investigation – stock return volatility on a year-by-year basis before conducting the full period analysis.

3.5 Statistical Analysis Techniques and Tests

In this research, three techniques were used to determine the effect of (size of the company which is represented in total assets, EPS and market-to-book value, interest rate, exchange rate, inflation rate and GDP) stock return volatility:

1 GLS using SPSS Version 22
2 GARCH using Eviews 10
3 Logit regression model using SPSS Version 22
4 ANN using Matlab statistical program.

Statistical analysis tests:

1 Normality test: fixed vs random
2 Different correlation coefficients (Spearman test)
3 Dickey–Fuller test to test the stationary or non-stationary data.
4 Root square error
5 Mean square error.

3.6 Study Hypotheses

1 There's a statistically significant relationship between the selected set of independent variables both internal (size of the company – represented by total assets, EPS and market-to-book value) and external (interest rate, exchange rate, inflation rate, GDP and stock return volatility using GLS regression
2 There's a statistically significant relationship between the selected set of independent variables both internal (size of the company – represented by total assets, EPS and market-to-book value) and external (interest rate, exchange rate, inflation rate, GDP and stock return volatility using GARCH model.
3 There's a statistically significant relationship between the selected set of independent variables both internal (size of the company – represented by total assets, EPS and market-to-book value) and external (interest rate, exchange rate, inflation rate, GDP and stock return volatility using ANN model.
4 ANN can achieve better predictive accuracy than the logit method in the classification of the stocks traded in the Egyptian exchange into "high volatility and low volatility".
5 There is no significant difference between the predictive accuracy of the neural network model and the competing statistical models – GLS and GARCH models.

4 Empirical Results and Testing Hypothesis

1 Hypothesis 1: There's a statistically significant relationship between the selected set of independent variables both internal (size of the company – represented by total assets, EPS and market-to-book value) and external (interest rate, exchange rate, inflation rate, GDP and stock return volatility using GLS Regression (Table 5.2)

Results have shown that the relationship between P-BV, mean stock return, int. rate, exchange rate, inflation rate and the standard deviation is significant with a positive sign as the corresponding *P*-values are less than 0.05 and correlation coefficients are 0.057, 0.084, 0.086, 0.118 and 0.171, respectively. The reported results also show that there is a

Table 5.2 Regression analysis

			Log-TA	*EPS*	*P-BV*	*Mean*	*Int rate*	*Exche rate*	*Inf rate*	*Log-GDP*	*STD*
Spearman's rho	**Log-TA**	**Correlation coefficient**	1.000								
		Sig. (2-tailed)									
		N	1390								
	EPS	**Correlation coefficient**	.247**	1.000							
		Sig. (2-tailed)	.000								
		N	1390	1390							
	P-BV	**Correlation coefficient**	−.105**	.045	1.000						
		Sig. (2-tailed)	.000	.092							
		N	1390	1390	1390						
	Mean	**Correlation coefficient**	.034	.049	.104**	1.000					
		Sig. (2-tailed)	.209	.067	.000						
		N	1390	1390	1390	1390					
	Int-rate	**Correlation coefficient**	−.002	−.042	−.173**	−.012	1.000				
		Sig. (2-tailed)	.953	.121	.000	.660					
		N	1390	1390	1390	1390	1390				
	Exchange rate	**Correlation coefficient**	−.037	−.088**	−.117**	−.044	.738**	1.000			
		Sig. (2-tailed)	.167	.001	.000	.098	.000				
		N	1390	1390	1390	1390	1390	1390			

Inflation rate	**Correlation coefficient**	−.003	−.070**	−.066*	−.101**	.238**	.363**	1.000		
	Sig. (2-tailed)	.899	.009	.013	.000	.000	.000			
	N	1390	1390	1390	1390	1390	1390	1390		
Log-GDP	**Correlation coefficient**	−.011	.034	−.021	−.009	−.011	−.008	.003	1.000	
	Sig. (2-tailed)	.681	.205	.428	.750	.669	.765	.911		
	N	1390	1390	1390	1390	1390	1390	1390	1390	
STD	**Correlation coefficient**	−.195**	−.067*	.057*	.084**	.086**	.118**	.171**	.041	1.000
	Sig. (2-tailed)	.000	.012	.034	.002	.001	.000	.000	.127	
	N	1390	1390	1390	1390	1390	1390	1390	1390	1390

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

significant negative relation between log-TA, EPS and standard deviation with corresponding *P*-values less than 0.05 and correlation coefficients of −0.195 and −0.067. Log of GDP is insignificant.

2 Hypothesis 2: There's a statistically significant relationship between the selected set of independent variables both internal (size of the company – represented by total assets, EPS and market-to-book value) and external (interest rate, exchange rate, inflation rate, GDP and stock return volatility using GARCH model) (Table 5.3).

Results have shown that the relationship between P-BV, int. rate, inflation rate, log-GDP and the standard deviation is significant with a positive sign as the corresponding *P*-values are less than 0.05 and correlation coefficients are 0.00, 0.0011, 0.000 and 0.0028, respectively. The reported results also show that there is a significant negative relation between log-TA and standard deviation with corresponding *P*-values less than 0.05 and correlation coefficients of −0. 0125. Mean, EPS and exchange rate are insignificant.

Table 5.3 GARCH model

Dependent variable: STD
Method: ML – GARCH (Marquardt) – normal distribution
Sample: 1 1390
Included observations: 1390
Convergence achieved after 468 iterations
Presample variance: backcast (parameter = 0.7)

$$GARCH = C(11) + C(12) \times RESID(-1)^2 + C(13) \times GARCH(-1)$$

Variable	Coefficient	Std. error	*z*-Statistic	Prob.
EPS	0.000140	0.000197	0.714601	0.4749
EXCHANGE_RATE	1.09E−05	0.000123	0.088767	0.9293
INFLATION_RATE	0.001170	0.000251	4.655937	0.0000
INT_RATE	0.112219	0.034410	3.261235	0.0011
LOG_GDP	0.008515	0.002851	2.986832	0.0028
LOG_TA	−0.001251	0.000306	−4.082456	0.0000
MEAN	0.024512	0.032034	0.765168	0.4442
P_BV	0.002680	0.000198	13.52461	0.0000
PRICE	0.000126	4.63E−05	2.722805	0.0065
C	−0.005691	0.008553	−0.665456	0.5058
	Variance equation			
C	5.22E−05	2.81E−06	18.56515	0.0000
$RESID(-1)^2$	0.645145	0.077737	8.299047	0.0000
GARCH(−1)	0.110321	0.030889	3.571484	0.0004
R-squared	−1.336088	Mean dependent var		0.022558
Adjusted *R*-squared	−1.351323	S.D. dependent var		0.010633
S.E. of regression	0.016304	Akaike info criterion		−6.321236
Sum squared resid	0.366840	Schwarz criterion		−6.272256
Log likelihood	4406.259	Hannan–Quinn criter.		−6.302920
Durbin–Watson stat	0.975247			

3 Hypothesis 3: There's a statistically significant relationship between the selected set of independent variables both internal (size of the company – represented by total assets, EPS and market-to-book value) and external (interest rate, exchange rate, inflation rate, GDP and stock return volatility "using ANN model".

After the preprocessing of the data set – a standard procedure in neural network application – the feed-forward neural network model, with one hidden layer was employed.

Since the complex weighting system is considered an integral part of the neural network, the standard coefficients of the independent variables measuring the nature and magnitude of their relative impact on the dependent variable are not produced in the standard output of neural network models.

The standard evaluation procedures followed when employing neural network models are presented as follows (Figures 5.2 and 5.3).

As shown in Figure 5.2, measures the joint effects of the independent variables (input variables) on the dependent variable (the output variable) and as such it resembles the coefficient of determination produced by the standard statistical models. The overall performance is equal to 49, 11% of which will be evaluated against the other traditional models (GLS and GARCH).

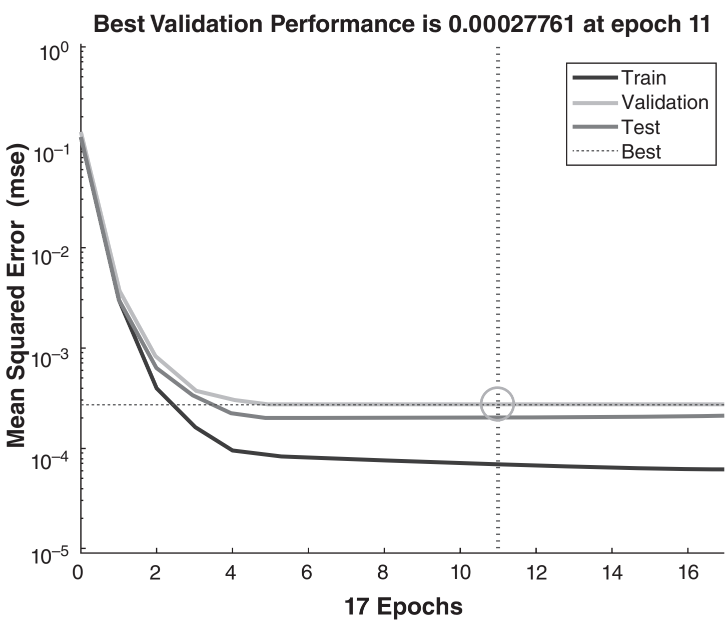

Figure 5.2 The mean square error (MSE) for the neural network model.

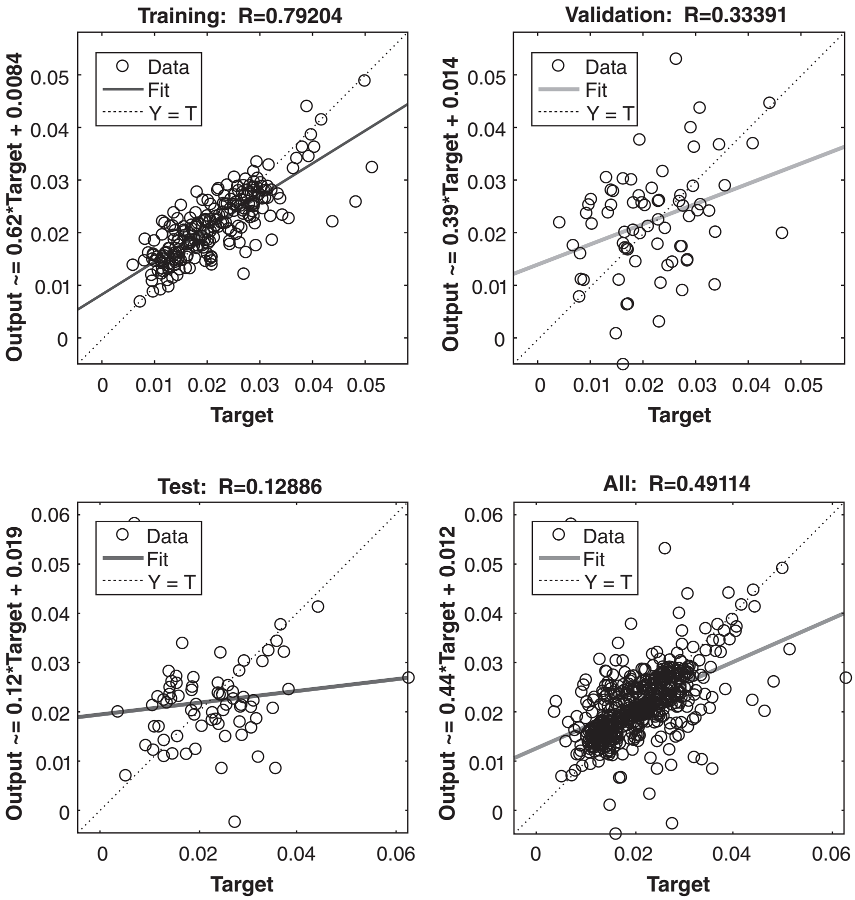

Figure 5.3 The fitted line produced by the neural network model.

Table 5.4 Matrix for neural network

Predicted actual	*High*	*Low*	*Total*
High	314 (51%)	303 (49%)	617 (100%)
Low	113 (13%)	750 (87%)	863 (100%)
Total	427	1053	1480

4 Hypothesis 4: ANN can achieve better predictive accuracy than the logit method in the classification of the level of volatility (high) and (low) for the Egyptian stocks.

The percentage of correct classification for the neural network model is 72 while the percentage of correct classification for the logit model

Table 5.5 Matrix for the logit model

Predicted actual	*High*	*Low*	*Total*
High	346 (56%)	271 (44%)	617 (100%)
Low	146 (19%)	699 (81%)	863 (100%)
Total	510	970	1480

Table 5.6 Comparative analysis of the three used models

Model name	*Value of MSE*
GLS	0.011
GARCH	0.008
ANN	0.002

is 70 which is illustrated in the two following matrices (Tables 5.4 and 5.5).

5 Hypothesis 5: There is no significant difference between the predictive accuracy of the neural network model and the competing statistical models – GLS and GARCH models (Table 5.6).

5 Conclusion

Regarding the size factor as represented by the log of total assets, several previous studies have examined the effect of company size on the stock return volatility. Cheung and Ng (1992) have studied stock price dynamics and firm size, and the results indicated that there was a negative relationship between company size and stock return volatility. In other words, the stocks of large companies tend to have much lower volatility than their smaller counterparts. Investors tend to retain stocks of large companies for a longer period as compared to their holdings of shares of smaller companies. This tendency contributes to the decrease in the volatility of stock returns of large companies. The findings of the current study confirm the existence of a significant negative impact of the company size on the stock return volatility.

On the other hand, the Bayo Olaoye et al. (2016) study revealed that the company size – total assets – has no significant impact on stock return volatility.

Regarding the EPS variable, several studies have indicated that there is a significant positive effect for EPS on stock return volatility. These studies include Hartono (2004) and Velankar et al. (2017), which reveal the existence of a significant positive relation between EPS and stock price volatility. These findings are in line with the findings of the current study.

As for the P/BV variable, few studies have examined its effect on stock return volatility. Among those studies is the study of Osundina et al. (2016)

which has investigated the impact of accounting information – including P/BV – on stock price volatility. The reported results are in line with the findings of the current study as both studies confirm the existence of a significant positive relation between P/BV and stock return volatility.

With regard to the mean stock return (mean), some previous studies examined its impact on stock return volatility. A leading study by Haugen (1991) has examined the effect of the level of stock return on the level of volatility of share prices. The reported results showed a negative relationship between the level of stock return and the level of volatility of share prices. This finding is incompatible with the findings of the current study, indicating that the mean stock return has a significant positive impact on the volatility of stock returns.

As for the inflation rate variable, several previous studies have examined its impact on stock return volatility. These studies include Erdem et al. (2005). The results of those studies show that there is a strong negative effect of the inflation rate on stock return volatility. The results of the current study confirm the findings of previous studies in the area. These studies concluded that it is helpful for investors to have a better understanding of the impact of inflation on market risk – as measured by return volatility when selecting the appropriate investment strategy.

Regarding the exchange rate and interest rate variables, a number of previous studies have investigated their relative impact on the stock return volatility. These studies include Kasman et al. (2011), Khalid (2017) and Nesrine et al. (2019). These studies have reported a significant negative impact on the stock return volatility. These results are in line with the findings of the current study.

For the GDP variable: many studies have studied the effect of GDP on stock return volatility and revealed a positive relation, but in our study, with given data, there's an insignificant effect of GDP on stock return volatility.

6 Recommendation and Further Research

6.1 Recommendation

1 Policymakers can use the findings of this study in the formulation of regulatory frameworks and market surveillance procedures designed to improve the functioning of the Egyptian stock market.
2 Policymakers should take into consideration the potential impacts of economic actions of the foreign countries on the level of volatility in the Egyptian stock markets and design appropriate policies to protect the Egyptian stock market from the potential impact of those actions.
3 Investors may use the findings of this study in their portfolio selection decisions since the two main criteria considered in the portfolio selection are risk (measured by volatility) and return.

4 Managers of investment funds and other institutional investors can use the findings of this study in the selection of appropriate securities to be included in their funds. Since most funds deal with risk tolerance objectives which are strongly related to the degree of stock return volatility.

6.2 Further Work

1 Further studies could advance our knowledge about other regions like the MENA region and other emerging markets such as Turkey, South Africa and India.
2 Comparative study should be conducted between developing and developed countries which will allow researchers to identify factors that affect stock return volatility in developed versus developing countries.
3 Further studies include the investigation of stock return volatility in periods of boom and recession in order to investigate the impact of the business cycle on the stock return volatility in various economic conditions.
4 Future studies on stock return volatility should be expanded to study the impact of economic reform programs on stock return volatility by comparing the level of volatility before and after the implementation of those reforms.
5 Further studies should include the impact of the level of foreign investors holding Egyptian shares and their actions (massive sales and massive purchases) on stock return volatility.
6 Future resear0ch should be expanded to include the potential impact of tax reforms including the capital gain tax on stock trading on the level of stock return volatility in the Egyptian stock market.

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6 Operation Analysis of Financial Sharing Center Based On Big Data Sharing Technology

Taking SF Express as an Example

Chengwei Zhang, Ge Guo, Weiqi Rao and Xinyan Li

1 Introduction

1.1 Research Background

With the continuous improvement of the international informatization level and the rapid development of the world economy, the increasing commercial trade also puts forward higher requirements on the financial management system of enterprises. Under such circumstances, many large and medium-sized enterprises usually have many problems, and the difficulties caused by financial management make the overall work efficiency of the enterprise inefficient. In order to solve these problems, the centralized management form of the financial shared service center came into being. The management model of the financial shared service center has comprehensively improved the quality and efficiency of corporate financial management and is an important means for the transformation and development of financial management under the new situation. As early as 2013, the Ministry of Finance of our country promulgated the "Enterprise Accounting Informatization Work Norms" clearly pointed out: large enterprises should explore the use of information technology to gradually establish financial shared service centers. Since then, the construction of the domestic financial sharing center has developed rapidly [1–4].

For logistics enterprises, information construction is the key to the development of the modern logistics industry. Therefore, the financial shared service center is imperative for the logistics industry. Since its establishment, SF Express has developed rapidly and is a leading representative express company characterized by "fast delivery". In recent years, SF Express has been able to develop rapidly due to the dividends of e-commerce. Taking into account the rapid increase in the number of SF Express's logistics business, coupled with the wide range of SF Express's express delivery business, branch offices are scattered in various regions of the country. SF Express's management and control capabilities are restricted. In order to change the status quo, SF Express has established a financial shared service center. This financial management model solves the problems existing in various

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financial processes of SF Express. So as to reduce the operating cost of the enterprise and meet the business needs of SF Express [5–7].

1.2 Research Significance

First of all, to help accountants to achieve a change in thinking. After ERP goes online, the thinking of financial people needs to be changed. FSSC is a company's "professional" financial management model, which came into being in the transformation of ERP's technical process. It requires accounting to focus on the "business cycle" and the smooth connection of the entire process steps from front-end business to back-end finance, instead of focusing on the accounting records of a single business transaction after the fact.

Secondly, provide support for corporate financial transformation. The process of applying "Internet +", "big data", "cloud computing", and "sharing" to financial management has resulted in the "financial sharing" model. The organization and management model of the financial shared service center has brought a revolution in the financial field. Over the years, market competition has become increasingly fierce, and corporate pressure has increased. More and more companies have joined the ranks of financial sharing services, providing more and more materials for the study of financial sharing centers. However, the financial sharing center does not have the best for different industries, only the most suitable. This chapter takes SF Express as an example to provide a reference for other similar companies in their financial transformation.

Finally, this chapter has a certain reference value for the upgrade and improvement of the financial shared service center of SF Express in reality. With the updating of new technologies, more new technologies are gradually replacing manual operations, and financial sharing should be in a trend of continuous innovation. Undoubtedly, various problems will be encountered in the process of innovation. Analyzing the financial shared service center of SF Express can make its financial shared service center better innovative and enable SF Express to maintain its leading position in the logistics industry [8].

1.3 Status of Domestic and Foreign Research

1.3.1 Research Status Abroad

Robert W. Gunn and others [1] put forward the concept of financial sharing earlier. They believe that shared management is an innovative management concept that can improve competitive advantage by centralizing and integrating resources. The IMA "Management Accounting Announcement" (2010) pointed out that the financial shared service center is an internal organization within the enterprise and is an independent part of the operation. Herbert and Seal [3] pointed out that the financial sharing center can not only help enterprises integrate their businesses and provide support internally, but also create value externally.

1.3.2 Research State in China

Gao Yanjun [4] believes that the design of the financial sharing center should meet its financial strategic goals. On the basis of achieving goals, combine business and human resources. Zhou Hui pointed out the need to perform performance management in the financial sharing center. Only in this way can we provide better services and improve work efficiency.

1.3.3 Literature Summary

Scholars focused on the definition of the financial shared service center, the process of reengineering information technology, the problems that occurred in the operation of the financial shared service center, and the cost-effectiveness. But it did not combine the process reengineering and performance evaluation of the financial shared service center for analysis. Therefore, the research on the process innovation of the financial shared service center under the background of big data is conducive to enriching the depth of financial management theory in shared services. Second, financial sharing is an innovation in financial management methods. The essence is also the reengineering of the process. A case study of the operation of the corporate financial shared service center under the background of big data provides some basis for the theoretical research of financial management.

2 SF Financial Sharing Center

2.1 Introduction to SF Express

SF Express was established in 1993 with a registered capital of approximately 150 million yuan and its headquarter is located in Shenzhen. Since its establishment, SF Express has been developing steadily and is a leading representative of express delivery companies characterized by "fast delivery". Due to national policies, the transformation of financial accounting, and the internal requirements of SF Express Group, SF Express established a financial shared service center in 2015.

2.2 The Construction Goals of SF Express Financial Sharing Center

The construction goal of SF Express financial shared service center is to optimize the financial management process. Before the sharing model of SF

Express, financial personnel in different regions had deviations in their understanding of the financial system. Problems such as inconsistent accounting treatment standards, inconsistent process operations, and inconsistent travel subsidy standards often occur. And in terms of expense reimbursement, salespersons often need to go to each audit port for offline audit item by item, and work efficiency and work quality will be affected to a certain extent. After the establishment of the financial shared service center of SF Express, the financial management process will be sorted out. First, abolish the system that conflicts with the group's regulations. Secondly, a unified system specification, reimbursement standards, and accounting standards have been established, and the personnel of the financial shared service center has been uniformly trained. Open up all system interfaces and write standardized operating procedures. Not only that, the establishment of the financial sharing center has made the communication between the financial department and the business units smoother. The financial department can better regulate the financial work in response to the feedback from the business unit. Moreover, in the financial management analysis work, you can also find the business unit to consider the problem based on the situation learned in the communication, so that the financial decision-making and business decision-making of the enterprise can be more scientific and reasonable.

2.3 The Construction History of SF Express Financial Shared Service Center

2.3.1 Establish a Standardized Basic Financial Processing Process

In order to unify the basic financial work of SF Express, it is first necessary to establish a standardized basic financial processing process. Realize that the basic financial work of SF Express Group's branches is concentrated in the financial shared service center for processing. This centralized processing method improves the status quo of low-end repetitive work performed by financial staff, for example, accounts receivable management and accounting, accounts payable management and accounting, expense reimbursement, collection and payment services, tax invoicing, and other basic financial tasks. After SF Express has established a standardized basic financial processing process, these businesses can be concentrated in the SF Express financial shared service center for processing (Figure 6.1).

2.3.2 Cooperate with UFIDA to Establish a Shared Platform

The construction of SF Express financial shared service center is based on the sharing platform of UFIDA, which builds an information platform that meets its own characteristics. The information systems used by the shared platform of SF Express financial shared service center

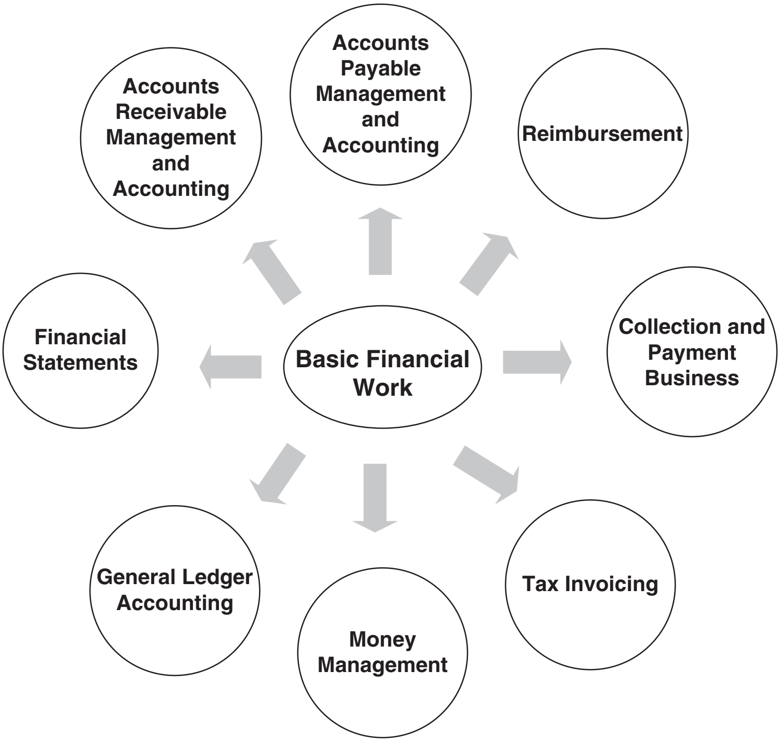

Figure 6.1 Basic financial work of SF Express financial shared service center.

include a financial ERP platform, professional financial system, and financial shared professional system. Among them, the financial ERP platform is mainly to generate a general ledger. The professional financial system includes fund management, budget management, consolidated statements, expense amortization, analysis, modeling, etc. Financial sharing professional systems include imaging systems, professional platforms, quality management, performance management, electronic invoice management, electronic file management, contract management, online accounting, etc. The establishment of the information platform and the realization of its functions are the prerequisites for the operation and management of the SF Express financial shared service center. SF Express financial shared service center successfully built an information platform and realized the normal functions of the information platform. The sound operation of the information platform of the SF Express financial shared service center has improved the efficiency of SF Express's operation and management. Improved the service quality of the SF Express financial shared service center and helped SF Express's management to make effective decisions (Figure 6.2).

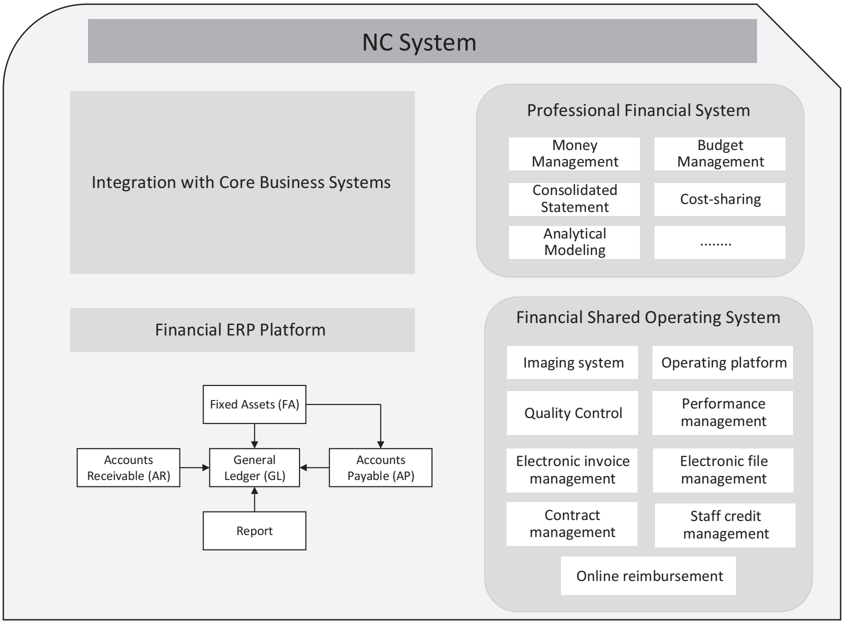

Figure 6.2 Shared platform of SF Express financial shared service center.

3 Achievements in the Construction of SF Financial Sharing Center

3.1 The Operating Costs of SF Express Continue to Decrease

The establishment of the SF Express financial shared service center has improved the financial working mechanism. This enables SF Express to obtain effective information when obtaining the most valuable information for the logistics industry in the era of big data, avoiding repeated information purchases. Effective use of funds to reduce the operating costs of SF Express. The SF Express financial shared service center can further increase the utilization rate of SF Express's financial information sharing, maximize the dynamic sharing of information transmission, and give play to the backing value of financial management in SF Express's market competition and financing. After the establishment of the financial shared service center, SF Express's operating costs, especially management expenses, have been continuously reduced. The administrative expenses in 2016 were 40.11 million yuan, while the administrative expenses in 2019 fell to 10.32 million, a decrease of 74.27%.

3.2 The Work Efficiency of SF Express Continues to Improve

Since the establishment of the financial shared service center, SF Express's financial management has been unified. SF Express financial shared service center has improved the status quo of low-end repetitive work performed by financial staff. Centralized management simplifies the work process, is more conducive to the standardization of business processes, improves various financial management tasks, and avoids inconsistent implementation in various regions. It has realized the automation of financial accounting mechanisms and the integration of financial analysis, reducing the disadvantages of reduced work efficiency due to different professional qualities. Secondly, the SF Express financial shared service center keeps abreast of financial information such as accounts receivable, accounts payable, bond relationships, and capital increase and decrease of each branch company, avoiding the occurrence of idle funds. The establishment of the SF Express financial shared service center has reduced the process of project funding declaration, enabled the project funds to arrive on time, and improved work efficiency. After SF Express established the financial shared service center, the number of financial personnel handling business has been reduced by 89 people compared with before, and the total cost has been saved about 2.83 million yuan.

3.3 The Management and Control Capabilities of SF Express Continue to Improve

The establishment of the financial shared service center changed the traditional financial management mode of SF Express in the past. This real-time monitoring of the financial shared service center model has enabled SF Express Group to continuously improve its management and control capabilities of its branches. SF Express financial shared service center has standardized procedures, operating standards, work efficiency, and risk management. This has changed the current financial management status of SF Express and strengthened the group's management and control capabilities. Secondly, it changed the way that SF Express submitted financial data of each branch in the past. The birth of SF Express financial shared service center enables SF Express to control the financial status of its branches in real time. When a branch of SF Express needs to face emergencies or internal faults, SF Express can make timely remedies based on the financial status of the branch reflected by the financial shared service center. In addition, the centralized management of cash transactions and bank transactions in the SF Express financial shared service center has reduced liquidity collection and payment activities and improved the stability of the company's capital. Through the direct monitoring of the SF Express financial shared service center and the bank, the internal financial information management and the control of financial activities of SF Express will be improved.

4 Comparison of SF Financial Sharing Center and Meicai Financial Sharing Center

In 2015, SF Express optimized the basic financial work process and prepared for the establishment of financial sharing. Finally, SF Express selected the location of the financial sharing service center in Wuhan. Beginning in July of the same year, SF Express took only 11 months to successfully collect basic financial tasks such as accounting, payables, payments, and statements to Wuhan Financial Sharing and completed the collection of hundreds of financial account sets across the entire network at that time. In the past 2 years, the number of shared business orders of SF Express has grown by an average of 36% annually and a cumulative increase of 85%, while the number of financial sharing personnel has been reduced by 25%. That is, when only 75% of the people are used to do the original 185% of the workload, the unit efficiency has been increased by 145%, and the quality has also been significantly improved. The financial sharing model is very much in line with the current development stage of SF Express.

Meicai financial shared service center was established on September 23, 2016. Through the introduction of SSC information tools, the integration and coordination of business and finance are realized, and the matching and closed loop of "logistics, information flow, bill flow, and capital flow" are realized. After the establishment of the Meicai financial sharing center, the operating cost was reduced by 30% and the efficiency of business processing was significantly improved. In the first half of 2020, the total number of audited orders was 54,000, compared with 23,981 in the first half of last year, a growth rate of 125%. At the same time, in the first half of 2020, the cost of each reimbursement form decreased by about 50% compared with the first half of 2019.

The financial shared service center is very suitable for large-scale enterprise groups such as SF Express and Meicai with large business volume and business coverage in Guangdong. If you want to solve the current problems in financial management, those similar enterprise groups may wish to consider establishing a financial shared service center.

5 Conclusion

Nowadays, financial sharing services are still of strategic significance for the transformation of financial management and the improvement of the classification of financial indicators. The financial shared service center is a management model that adapts to the times, which is of great benefit to the development of large enterprise groups. Through the analysis of this chapter, I hope it will be helpful to the future development of SF Express financial shared service center and hope to provide a certain reference value for other enterprise groups to implement and improve the financial shared service center.

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7 Optimization algorithms for multiple-asset portfolios with machine learning techniques

Theoretical foundations of optimum and coherent economic capital structures

Mazin A. M. Al Janabi

1 Introduction

In the last two decades, there has been a spectacular progress in the development and applications of machine learning techniques in many industrial settings, including financial markets and institutions and the Internet of things (IoT). The financial service industries have been one of the early enterprises that embraced artificial intelligence and its machine learning subfield. This comes as no surprise since financial markets and institutions have a long history of employing state-of-the-art modeling techniques and algorithms to examine important datasets and make rational decisions—ranging from stochastic differential equations, stochastic volatility models in portfolio and risk management, quadratic programming in Markowitz's portfolio optimization (Markowitz, 1959), and many other cases in quantitative finance.

Machine learning for financial applications and the policymaking process sits at the crossroads of many evolving and recognized disciplines including dynamic programming, probabilistic programming, signal processing, financial econometrics, stochastic processes, statistical computing, and so on. Since its earliest days as a sub-discipline of artificial intelligence, machine learning has taken advantage of optimization techniques and algorithms. Similarly, machine learning principles have influenced the optimization field, driving the progress in robust optimization techniques that tackle the important challenges put forward by machine learning uses and applications for many industrial settings, including machine learning for the policymaking process and the IoT. Likewise, optimization techniques and algorithms have gained importance in machine learning applications because of their large industrial applicability and desirable theoretical characteristics.

While optimization algorithms and techniques devised earlier continue to be improved, the risen complexities in financial markets and the impact of financial crises as evidenced in the wake of the 2007–2009 meltdown, and the range of current machine learning modeling approaches for the

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policymaking process demand a reexamination of prevailing optimization techniques and suppositions for risk management and portfolio selection under adverse markets circumstances. One of these rising fields in risk management and portfolio selection is the application of robust machine learning and optimization algorithms for multiple-asset portfolios under illiquid market conditions subject to meaningful financial and operational constraints, and this is the main focus of this chapter.[1]

In this backdrop, academics and practitioners have long acknowledged the significance of assessing the market risk of multiple-asset portfolios of financial and/or commodity securities. In recent years, the growth of trading activities and instances of financial/commodity market upheavals has prompted new research underlining the necessity for market participants to develop reliable dynamic portfolio management and risk assessment methods and algorithms. In measuring the market risk of trading portfolios, one technique advanced in the literature involves the use of value at risk (VaR) models that ascertain how much the value of a trading portfolio would plunge, in monetary terms, over a given period of time with a given probability as a result of changes in market prices (Philippe, 2001; Hull, 2009). Nowadays, VaR is by far the most popular and most accepted risk measure among financial institutions; however, whether or not there is the best way to estimate VaR is still debatable. Although VaR is a very popular measure of the market risk of financial trading portfolios, it is not a panacea for all risk assessments and has several drawbacks, limitations, and undesirable properties (Sanders, 2002; Al Janabi, 2012, 2013, 2014). From a portfolio market risk point of view, VaR faces some major difficulties. Three of the most researched and discussed issues are the non-normal behavior of asset returns, volatility clustering, and the impact of illiquid assets. The effect of the latter on portfolio risk management and dynamic economic capital allocation under market liquidity constraints is the aim of this chapter.

Indeed, methods for measuring market (price or trading) risk have been well developed and standardized in the academic as well as the financial services industry. Asset liquidity trading risk, on the other hand, has received less attention from researchers, perhaps because it is less significant in developed countries where most of the market risk methodologies originated. In all but the most simple of circumstances, comprehensive metrics of liquidity trading risk management do not exist explicitly within modern portfolio theory (Al Janabi, 2012, 2013, 2014). Nonetheless, the combination of the recent rapid expansion of emerging markets' trading activities and the recurring turbulence in those markets, in light of the aftermaths of the 2007–2009 sub-prime financial crisis, has propelled asset liquidity trading risk to the forefront of market risk management research and development (Al Janabi, 2008). Likewise, the 2007–2009 financial crisis shows that asset liquidity risk played a major role in, for example, the bankruptcy of Lehman Brothers and Bear Stearns; and also played a big role in the demise of Long-Term-Capital-Management (LTCM). As such, asset liquidity risk became in recent times of particular concern in developed financial markets as well.

In effect, the conventional VaR approach to computing the market risk of a portfolio does not explicitly consider asset liquidity risk. Typical VaR models are based on modern portfolio management theory and assess the worst change in the value of the mark-to-market portfolios over a given time horizon; however, they do not account for the actual trading risk of liquidation (Al Janabi, 2013, 2014). In general, customary fine-tunings are made on an ad hoc basis. At most, the holding period (closeout or liquidation horizon) over which the VaR figures are computed is adjusted to ensure the inclusion of liquidity risk. As a result, liquidity trading risk can be imprecisely factored into VaR assessments by assuring that the liquidation horizon is as a minimum larger than an orderly liquidation interval. Moreover, the same closeout horizon is employed for all trading asset classes, albeit some assets may be more liquid than others. Without a doubt, neglecting asset liquidity risk can lead to an underestimation of the overall market risk and misapplication of capital cushion for the safety and soundness of financial markets and institutions. In emerging financial markets, which are relatively well considered illiquid, ignoring liquidity risk can result in a significant underestimation of VaR, especially under extreme events market forecasts (Al Janabi, 2008). As a result, the increase in the traceability of equities in emerging markets necessitates a reexamination of current market and liquidity risk management modeling techniques, specifically for investment funds with trading portfolios—of either long-only holdings or combinations of long- and short-sale trading positions—and within short horizons of re-balancing and reporting focuses.

In contrast to all existing published literature pertaining to the application of machine learning (e.g. Ban et al., 2018; Kalayci et al., 2019; Paiva et al., 2019), the use of machine learning techniques for the policymaking process and for the IoT data analytics to risk analysis and optimization of multiple-asset portfolios, our proposed risk engine and optimization algorithm differ in important ways from previous, however, related research. To that end, this chapter provides portfolio risk management techniques and strategies (drawn from financially meaningful investment considerations) that can be applied to equity trading portfolios in emerging and developed markets. The key methodological contribution is a different and less conservative liquidity-scaling factor than the conventional root-t multiplier. The proposed add-on is a function of a predetermined liquidity threshold defined as the maximum position that can be unwound without disturbing market prices during one trading day. In addition, the re-engineered model is quite robust to be implemented even by very large financial institutions with multiple-asset and risk factors. In fact, the essence of the modeling algorithm relies on the assumption of a stochastic stationary process and some rules of thumb, which can be of crucial value for more accurate market risk quantification under illiquid market scenarios. In this chapter, we attempt to integrate and estimate the impact of liquidity trading risk into VaR models by explicitly integrating the impact of the time-volatility dimension of liquidity risk instead of the movements in the bid-ask spread. The approach to assessing liquidity-adjusted value at risk (L-VaR) for distinctive equity portfolios has been illustrated with the help of a modified closed-form parametric modeling algorithm, where conditional volatilities and expected returns are estimated with the aid of a generalized autoregressive conditional heteroscedasticity in mean [GARCH-M (1,1)] model.

2 Key principles of current research and literature review

Portfolio optimization and dynamic asset allocation have come a long way from the Markowitz (1959) mean-variance risk management framework. The developments in portfolio optimization techniques are stimulated by two basic requirements: a proper modeling of utility functions, risk measures, and budget constraints and the second requirement is related to the efficiency of the algorithms in handling a large number of securities and asset allocation scenarios. In fact, there are two basic approaches to the problem of portfolio selection under uncertainty. One approach is based on the concept of utility theory. While this approach offers a quantitatively rigorous treatment of the portfolio selection process, it appears now and then detached from the real world of asset management. The other approach is the risk-return analysis; and according to it, the portfolio choice is made with respect to two criteria: the expected return and portfolio risk. As a result, different portfolios can be simulated and a portfolio is preferred to another one if it has a higher expected return and lower risk. In fact, the simplicity and the intuitive appeal of portfolio construction using modern portfolio theory have attracted significant attention both in academia and in practice. Yet, despite considerable effort, it took many years until portfolio managers started using modern portfolio theory for managing real money. Unfortunately, in real-world applications, there are many problems associated with it, and portfolio optimization is still considered by many practitioners to be difficult to apply (Fabozzi et al., 2006).

Indeed, since the commencement of modern finance theory, there is a constant debate on the concept of risk and a rising awareness of ways to measure it and to manage it properly. This controversy has gone along with a growing investment in portfolio models, based on sophisticated quantitative methods, which require an enormous computing power. One should not be surprised by this reality given that financial markets are now much more volatile and the use of derivative securities such as options and futures contracts, for hedging and speculation purposes, requires continuous developments in finance and investment modeling. In particular, the development of new modeling methods and optimization algorithms for portfolio risk management is now an overriding issue in the financial and academic communities.

In general terms, financial risks are usually associated with possible losses in financial markets arising from changes in the price of equities, currencies, and interest rates, but also risks associated with negative changes in the price of commodities, such as crude oil prices. The computation of financial risks has greatly evolved in the last three decades, from a simple indicator of market value, through more complex internal models such as scenario analysis to modern stress-testing and VaR measures. Current regulations for financial markets and institutions formulate some of the risk management requirements in terms of percentiles of loss distributions, and VaR is basically an upper percentile of the loss distribution.

VaR has become a useful tool for monitoring risk, and its use is being encouraged by the Bank for International Settlements (BIS) and Basel II and Basel III committees on banking supervision. In essence, VaR estimates the downside risk of a portfolio of market-priced assets at a particular confidence level over a chosen time horizon. In effect, VaR strives to assess adverse events in the lower tail of a return distribution of multiple-asset trading portfolios—events likely to cause financial distress to a firm if they arise. Because VaR concentrates solely on downside risk (or bad outcomes) and is typically articulated in dollars term, it is regarded as an insightful and transparent risk assessment tool for top-level management. The recognition of VaR as a risk assessment tool has triggered ample interest among risk management practitioners and academics alike. Notwithstanding the obvious uses of VaR for risk disclosure and reporting purposes, VaR has also been suggested for enterprise-wide risk management because of its ability to aggregate risk across asset classes. In essence, VaR could be valuable in making asset allocation and hedging decisions, managing cash flows, setting upper trading limits, risk budgeting, and overall portfolio selection and evaluation.

Despite many criticisms and limitations of the VaR method, it has proven to be a very useful measure of market risk and is widely used in financial and non-financial markets. Evidently, the overwhelming emphasis on VaR techniques has come from the finance literature, mostly as it pertains to the needs of entities to satisfy regulatory requirements. Based on studies to date, there is little agreement as to the best method for developing VaR risk measures. However, literature related to VaR is continually growing as researchers attempt to reconcile several pending issues. The prior literature on VaR and portfolio risk management has been focused on two distinct lines of research. The first category focuses mainly on the use of different VaR models for market and credit risk management and for selecting optimum portfolios within the VaR framework, whereas the second category emphasizes the development of asset liquidity risk as an integral part of market risk and, therefore, leads to several attempts for the estimation of L-VaR. Below we discuss some of the relevant literature classified according to the above two categories.

2.1 Literature related to optimum portfolio selection within a VaR structure

The literature on measuring financial risks and volatility using VaR models is extensive, yet Philippe (2001) and Dowd et al. (2004) should be pointed out for their integrated approach to the topic. The general recognition and use of large-scale VaR models have initiated considerable literature including statistical descriptions of VaR and assessments of different modeling techniques. For a comprehensive survey, and the different VaR analyses and techniques, one can refer to Philippe (2001).

On another front, other authors have investigated the use of VaR for the selection of optimum portfolios and for active portfolio management. For instance, Campbell et al. (2001) develop an optimum portfolio selection model that maximizes expected return subject to a downside risk constraint rather than standard deviation alone. The suggested model allocates multiple financial assets by maximizing expected return conditional on the constraint that the expected maximum loss should be within the VaR limits set by the risk manager. Additionally, the authors develop a performance index similar to the Sharpe ratio, which for the special case when expected returns are assumed to be normally distributed, provides almost identical results to the mean-variance approach. As such, the empirical analysis has been provided by using two risky assets, US stocks and bonds, and the empirical results underline the impact of both non-normal characteristics of the expected return distribution and the length of investment time horizon on the optimum portfolio selection process.

In another study, Yiu (2004) examines the optimum portfolio problem by imposing VaR as a dynamic constraint. This approach provides a path to control risks in the optimum portfolio and to satisfy the requirement of regulators on the assessment of market risks. Furthermore, the VaR constraint is derived for some risky assets plus a risk-free asset and is imposed continuously over time and the problem is formulated as a constrained utility maximization problem over a period of time. To this end, a dynamic programming technique is applied to derive the Hamilton–Jacobi–Bellman (HJB) equation and the method of Lagrange multiplier has been applied to handle the constraint. Moreover, a numerical method is proposed to solve the HJB equation and hence the constrained optimum portfolio. Under this formulation and the obtained numerical results, the author argues that investments in risky assets are optimally reduced by the imposed VaR constraint. This is because the VaR constraint is applied over time so that there is a direct relationship between the VaRs and portfolio holdings at each point in time.

In their paper, Alexander and Baptista (2004) analyze the portfolio selection implications arising from imposing a VaR constraint as a risk management tool on the mean-variance model and compare them with those arising from applying a conditional value-at-risk (CVaR) constraint. The authors find that under certain conditions, the presence of a VaR constraint causes a slightly risk-averse agent to select a portfolio that has a smaller standard deviation than the one that would have been selected in its absence. Furthermore, the authors show that for a given confidence level, a CVaR constraint is tighter than a VaR constraint if the CVaR and VaR bounds coincide. Consequently, a CVaR constraint is more valuable than a VaR constraint as a risk management tool to control slightly risk-averse agents. However, in the absence of a risk-free security, it has a perverse outcome in that it forces highly risk-averse agents to choose portfolios with larger standard deviations. However, when the CVaR bound is suitably superior to the VaR bound or when a risk-free security is available, a CVaR constraint "dominates" a VaR constraint as an effective risk management tool.

On the other hand, Alexander and Baptista (2008) look at the impact of adding a VaR constraint to the problem of an active manager who seeks to outperform a benchmark by a given percentage. In doing so, the authors minimize the tracking error variance (TEV) by using the model of Roll (1992). As such, the authors obtain three main results. First, portfolios on the constrained mean-TEV boundary still display three-fund separation; however, the weights of the three funds when the constraint binds differ from those in Roll's model. Second, the VaR constraint mitigates the problem that when a manager seeks to outperform a benchmark using the mean-TEV model, he or she selects a portfolio that is mean-variance inefficient. Finally, when short sales are not permitted, the extent to which the constraint decreases the optimum portfolio's efficiency loss can still be noteworthy but is less significant than when short sales are permitted. Indeed, their results on the usefulness of a VaR constraint justify the belief that the fund management industry is increasingly using VaR to (1) allocate assets among managers, (2) set risk limits, and (3) monitor asset allocations and managers.

In a similar vein, Cain and Zurbruegg (2010) propose a technique that involves switching between risk measures in different market environments to capture the well-documented dynamic nature of risk within a portfolio optimization setting. Thus, the in-sample results show categorically that switching between various measures, such as CVaR, time-varying (GARCH) variances, and simple standard deviations, can lead to a better performance than using any single measure.

2.2 Literature related to L-VaR modeling technique

Liquidity trading risk is a key concern for anyone holding a portfolio of any type of trading assets and liquidity crises proved to be imperative in the failure of many financial entities worldwide. More specifically, liquidity trading risk arises from situations in which a party interested in trading certain assets cannot do it because no one in the market wants to trade those assets. Thus, assets liquidity risk becomes for the most part important to financial market participants who are about to hold or currently holding certain assets, since it affects their ability to trade or unwind the trading positions. Insolvencies often occur because financial entities cannot get out or unwind their holdings effectively and, hence, the liquidation value of assets may differ significantly from their current mark-to-market values.

As such, the combination of the latest swift expansion of trading activities in emerging markets' and the persistent turbulence in those markets has impelled liquidity trading risk to the vanguard of market risk management research and development. To that end, within the VaR framework, Jarrow and Subramanian (1997) provide a market impact model of liquidity by considering the optimum liquidation of an investment portfolio over a fixed horizon. They derive the optimum execution strategy by determining the sales schedule that maximizes the expected total sales values, assuming that the period until liquidation is given as an exogenous factor. The correction to the lognormal VaR they derive depends on the mean and standard deviation of an execution lag function and of a liquidation discount. Although the model is simple and intuitively appealing, it suffers from practical difficulties in its implementation. It requires the estimation of additional parameters such as the mean and the standard deviation of the discount factor and the period of execution—for which data are not readily available, none of which may be easy to estimate and may require subjective estimates such as a trader's intuition.

Bangia et al. (2001) approach liquidity risk from another angle and provide a model of VaR adjusted for what they call exogenous liquidity—defined as common to all market players and unaffected by the actions of any one participant. It comprises such execution costs as order processing costs and adverse selection costs resulting in a given bid-ask spread faced by investors in the market. On the contrary, endogenous liquidity is specific to one's position in the market, depends on one's actions, and varies across market participants. It is mainly driven by the size of the position: the larger the size, the greater the endogenous illiquidity. They propose splitting the uncertainty in the market value of an asset into two parts: a pure market risk component arises from asset returns and uncertainty due to liquidity risk. Their model consists of measuring exogenous liquidity risk, computed using the distribution of observed bid-ask spreads and then integrating it into a standard VaR framework.

On another front, Berkowitz (2000) argues that unless the likely loss arising from liquidity risk is quantified, the models of VaR would lack the power to explicate the embedded risk. In practice, operational definitions vary from volume-related measures to bid-ask spreads and to the elasticity of demand. The author asserts that elasticity-based measures are of most relevance since they incorporate the impact of the seller actions on prices. Moreover, under certain conditions, the additional variance arising from seller impact can easily be quantified given observations on portfolio prices and net flows, and that it is possible to estimate the entire distribution of portfolio risk through standard numerical methods.

In his research papers, Al Janabi (2008, 2012, 2013, 2014) establishes a practical framework for the measurement, management, and control of trading risk and tackles the issue of adverse market price impact on liquidity trading risk and coherent portfolio optimization using a closed-form parametric L-VaR methodology. The effects of illiquid assets, which are dominant characteristics of emerging markets, are also incorporated into the risk modeling algorithms. These studies provide real-world risk quantitative management techniques and strategies (drawn from a practitioner viewpoint) that can be applied to equity trading portfolios in emerging markets. The intent is to propose a robust technique for including liquidation trading risk in standard VaR analysis and to capture the liquidity risk arising due to illiquid trading positions by obtaining an L-VaR estimation. The proposed adverse price unwinding approach comprises a liquidation multiplier (add-on) that can adjust the impact of unfavorable price movement throughout the closeout period along with an optimization algorithm that allocates assets subject to imposing meaningful financial and operational constraints.

Furthermore, in their research paper, Madoroba and Kruger (2014) introduce a VaR model that incorporates intraday price movements on high–low spreads and adjusts for a trade impact measure, a novel sensitivity measure of price movements due to trading volumes. Furthermore, the authors compare and contrast ten worldwide-recognized liquidity risk management models including the "Al Janabi model," which is used in this chapter for liquid risk modeling and for optimizing economic capital and coherent portfolios.

In a different modeling technique, Al Janabi et al. (2017) propose a portfolio optimization methodology based on the integration of DCC (dynamic conditional correlation) *t*-copula and L-VaR models to enhance asset allocation decisions under illiquid market conditions. Their empirical findings prove the superiority of the DCC-copula-L-VaR modeling technique over the traditional Markowitz (1959) optimization procedure for a portfolio composed of international stock market indices, gold, and crude oil across various trading scenarios[2]. In a similar vein, Al Janabi, Ferrer, and Shahzad (2019) develop a novel approach to assess L-VaR optimization of multi-asset portfolios based on vine copulas and L-VaR models. This framework is applied to stock markets of the G-7 countries, gold, commodities, and Bitcoin. The results show that our approach is superior to the classical mean-variance Markowitz portfolio technique in terms of the optimal portfolio selection under a number of realistic operational and budget constraints.

2.3 Foundation and objective of current research

This chapter aims to model liquidity risk arising due to illiquid trading positions and to propose optimization algorithms for the computation of

L-VaR and coherent economic capital. In contrast to all existing published literature pertaining to the application of L-VaR and economic capital methods to financial and commodity markets, this chapter proposes a robust model for assessing a closed-form parametric L-VaR with an explicit treatment of liquidity trading risk. The main contribution of this chapter, to the fields of machine learning, financial engineering, machine learning for the policymaking process, and machine learning techniques for the IoT data analytics is to extend VaR computation to allow for a steady liquidation of multiple-asset portfolios over the holding period and by showing that liquidity risk can be straightforwardly and intuitively integrated into the quantitative framework of L-VaR. Rather than modeling liquidity trading risk as such, the central focus of this work is to develop a dynamic framework for the computation of liquidity risk and coherent economic capital allocation in the overall assessment of trading risk. Its essence relies on the assumption of a stochastic stationary process and some rules of thumb, which can be of crucial value for more accurate market risk assessment during market stress periods and when liquidity dries up. The liquidity modeling algorithm presented in this chapter does not incorporate all the aspects of liquidity trading risk. However, it is effective as a tool for evaluating trading risk and economic capital when the impact of illiquidity of specified financial products is significant.

The modeling techniques and optimization algorithms are interesting in terms of theory as well as for key practical applications and can have many uses and applications in financial markets, particularly in light of the 2007–2009 global financial meltdown. In addition, the implemented optimization techniques and risk assessment algorithms can aid in advancing risk management practices in emerging and developed markets, particularly in light of the 2007–2009 financial turmoil. Moreover, the proposed computational techniques and risk reporting process can have key uses and applications in machine learning and artificial intelligence, machine learning for the policymaking process, expert systems, smart financial functions, IoT, and financial technology (FinTech) in big data environments. Furthermore, it provides key practical modeling algorithms for portfolio and risk managers, treasury directors, risk management executives, policymakers, and financial regulators to comply with the requirements of Basel III best practices on liquidly risk and capital adequacy.

The balance of the chapter proceeds as follows. Section 3 lays out the salient features and derives the essential quantitative risk management background of the Al Janabi model, L-VaR, and optimization algorithms. First, we show that L-VaR can be derived for a single-asset portfolio assuming uniform liquidation over the holding period (closeout horizon). We then derive a general and robust modeling algorithm that incorporates the effects of multiple illiquid assets in market and liquidity risk management by simply scaling the multiple-asset vectors of L-VaR. This section also discusses the various parameters required for the optimization engine and the construction of efficient and coherent portfolios for long-only and long/short-sale trading positions and includes a graphical flowchart, which shows a concise outline of the risk engine's operational stages and their interrelationships. This flowchart highlights the required input parameters for portfolio optimization and selection and can aid in defining the processes for computer programming, machine learning and artificial intelligence, machine learning for the policymaking process, and machine learning techniques for the IoT data analytics. Section 4 concludes the chapter.

3 Theoretical foundations of Al Janabi model, L-VaR, and economic capital optimization algorithms for dynamic portfolio risk management and machine learning[3]

3.1 General closed-form parametric L-VaR algorithms for trading risk management

One of the most significant advances in the past three decades in the field of measuring and managing financial risks is the development and the ever-growing use of VaR methodology. VaR has become the standard measure that financial analysts use to quantify financial risks including equity risk. VaR represents the potential loss in the market value of a portfolio of equities with a given probability over a certain time horizon. The main advantage of VaR over other risk quantitative measures is that it is theoretically simple. As such, VaR can be used to summarize the risk of an individual equity position or the risk of large portfolios of equity assets. Thus, VaR reduces the risk associated with any portfolio of equities (or other multiple-asset) to just one number—the expected potential loss associated with a given probability over a defined holding period (Al Janabi, 2008, 2014).

VaR is being embraced by corporate risk managers as an important tool in the overall risk management process. In particular, upper-level managers, who may or may not be well versed in statistical analysis, view VaR as an intuitive measure of risk since it concentrates only on adverse outcomes and is usually reported in dollars term. However, initial interest in VaR stemmed from its potential applications as a regulatory tool. Because of this, VaR is commonly used for internal risk management purposes (e.g. setting trading limits among traders) and is further being touted for use in risk management decision making by non-financial firms. In the case of a non-financial firm, such as an energy enterprise, a risk manager may examine the VaR associated with a portfolio of risky assets (e.g. cash positions) prior to and after risk management strategies (e.g. use of futures, options, forward contracts, or combination of the above) are implemented. This allows the risk manager to assess the potential large losses to the portfolio in the presence of various risk management strategies, thus allowing the risk manager to more efficiently implement these strategies (Al Janabi, 2008, 2012, 2013, 2014).

In essence, VaR is intended to measure, with a given probability, the largest expected amount of money a position or trading portfolio could lose (with a given degree of confidence) over a given time horizon and under normal market conditions. Assuming the return of a financial product follows a normal distribution, linear pay-off profile, and a direct relationship between the underlying product and the income, the VaR measures the standard deviation of the trading income, which results from the volatility of the different markets, for a certain confidence level. This definition gives latitude in choosing both the confidence level and the time horizon. In practice, however, many financial and non-financial entities have chosen a confidence interval of 95% (or 97.5% if we only look at the "one-tailed" loss side) for their overall portfolio and a one-day time horizon to compute VaR. This means that once every 40 trading days a loss larger than indicated is expected to occur. Some entities use a 99% "one-tailed" confidence interval, which would theoretically lead to a larger loss once every 100 trading days. Due to fat tails of the probability distribution, such a loss will occur more often and can cause problems in computing VaR at higher confidence levels. Some entities feel that the use of a 99% confidence interval would place too much trust on the statistical model and, hence, some confidence level should be assigned to the "art-side" of the risk measurement process. Although the method relies on many assumptions and has its drawbacks, it has gained wide acceptance for the quantification and aggregation of trading risks. Because of the generalization of this method, economic capital allocations for trading and active investment activities tend to be computed and adjusted with the VaR method (Al Janabi, 2008, 2012).

To compute VaR using the variance/covariance (also known as the parametric, analytical, and delta-neutral) method, the conditional volatility of each risk factor is extracted from a pre-defined historical observation period and can be estimated using GARCH-M (1,1) model. The potential effect of each component of the portfolio on the overall portfolio value is then worked out. These effects are then aggregated across the whole portfolio using the correlations between the risk factors (which are, again, extracted from the historical observation period) to give the overall VaR value of the portfolio with a given confidence level. As such, for a single trading position the absolute value of VaR can be defined, in monetary terms, as follows (Al Janabi, 2013, 2014):

$$\text{VaR}_i = |(\mu_i - \alpha \times \sigma_i)(\text{mark-to-market value of asset}_i \times Fx_i)| \tag{1}$$

where μ_i is the expected return of the asset, α is the confidence level (or in other words, the standard normal variant at confidence level α) and σ_i is the conditional volatility of the return of the security that constitutes the single position and can be estimated using a GARCH-M (1,1) model. While the mark-to-market value of asset$_i$ indicates the amount of investment in asset

i, Fx_i denotes the unit foreign exchange rate of asset i. If the expected return of the asset, μ_i is very small, then equation (1) can be reduced to:

$$\mathrm{VaR}_i = |\alpha \times \sigma_i \times \text{mark-to-market value of asset}_i \times Fx_i| \tag{2}$$

Indeed, equation (2) includes some simplifying assumptions, yet it is routinely used by researchers and practitioners in the financial markets for the estimation of VaR for a single trading position.

Trading risk in the presence of multiple risk factors is determined by the combined effect of individual risks. The extent of the total risk is determined not only by the magnitudes of the individual risks but also by their dependence measures (i.e. correlations parameters). Portfolio effects are crucial in risk management not only for large diversified multiple-asset portfolios but also for individual instruments that depend on several risk factors. For multiple-asset, VaR is a function of the risk of each specific asset and the correlation factor $[\rho_{i,j}]$ between the assets returns, as follows[4]:

$$\mathrm{VaR}_P = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} \mathrm{VaR}_i\ \mathrm{VaR}_j\, \rho_{i,j}} = \sqrt{[\mathrm{VaR}]^T\ [\rho]\,[\mathrm{VaR}]}$$

This formula is a general one for the calculation of VaR for any portfolio regardless of the number of securities. It should be noted that the second term of the above formula is rewritten in terms of matrix-algebra—a useful form to avoid mathematical complexity, as more and more securities are added. This approach can simplify the programming and computational processes and permits the easy incorporation of short-sale positions in the market risk management process. This means, in order to compute VaR (of a portfolio of any number of securities), we need to generate first a transposed vector $[\mathrm{VaR}]^T$ of the individual elements of the VaR positions—an ($1 \times n$) vector, and hence, the superscript "T" indicates transpose of the vector, such as:

$$[\mathrm{VaR}]^T = [\mathrm{VaR}_1\ \ \mathrm{VaR}_2\ \ \ldots\ldots.\ \ \mathrm{VaR}_n] \tag{3a}$$

Second, a vector [VaR] of the individual elements of the VaR positions—explicitly n rows and one column ($n \times 1$) vector, such as:

$$[\mathrm{VaR}] = \begin{bmatrix} \mathrm{VaR}_1 \\ \mathrm{VaR}_2 \\ \ldots.. \\ \mathrm{VaR}_n \end{bmatrix} \tag{3b}$$

Finally, a matrix $[\rho]$ of all correlation factors (ρ)—an ($n \times n$) elements matrix in the following form:

$$[\rho] = \begin{bmatrix} 1 & \rho_{1,2} & \rho_{1,3} & \cdots\cdots & \rho_{1,n} \\ \rho_{2,1} & 1 & \rho_{2,3} & \cdots\cdots & \rho_{2,n} \\ \rho_{3,1} & \rho_{3,2} & 1 & \cdots\cdots & \rho_{3,n} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \rho_{n,1} & \rho_{n,2} & \rho_{n,3} & \cdots\cdots & 1 \end{bmatrix} \tag{3c}$$

Therefore, the multiplication process of the elements of the two vectors and dependence matrix leads to the computation of VaR_P for portfolios with any n-number of assets. This simple number summarizes the portfolio's exposure to market risk. Investors and senior managers can then decide whether they feel comfortable with this level of risk exposure. If the answer is no, then the process that led to the estimation of VaR can be used to decide where to reduce redundant risk. For instance, the riskiest assets may be sold, or one can use derivative securities such as futures and options contracts on equities to hedge the undesirable risk exposures (Al Janabi, 2008, 2012, 2013, 2014).

In effect, the VaR method is only one approach of measuring market risk, and it is mainly concerned with the maximum expected losses under normal market outlooks. It is not an absolute measure, as the actual amount of loss may be greater than the given VaR amounts under stressed market circumstances. In extreme situations, VaR models do not function very well. As a result, firms need to boost VaR assessment with stress-testing and scenario analysis. From a risk management perspective, however, it is desirable to have an estimate for what potential losses could be under adverse conditions, where traditional statistical tools do not apply. As such, stress-testing estimates the impact of unusual and severe events on the entity's value and should be reported on a daily basis as part of the risk management reporting process. For emerging economies with extreme levels of volatility, the use of stress testing should be highly emphasized and a full description of the process is included in any trading risk policy and procedures manuals. Stress testing usually takes the form of subjectively specifying scenarios of interest to assess changes in the value of the portfolio and it can involve examining the effect of past large market moves on today's portfolio (Al Janabi, 2008, 2012, 2013, 2014).

3.2 Integrating asset liquidity risk into L-VaR modeling techniques

Illiquid securities such as foreign exchange rates and equities are very common in emerging markets. Customarily these securities are traded infrequently (at very low volume). Their quoted prices should not be regarded as a representative of the traders' consensus vis-à-vis their real value but rather as the transaction price arrived at by two counterparties under special market conditions. This of course represents a real dilemma for anybody who seeks to measure the market risk of these securities with a methodology that is based on volatilities and correlation matrices. The main problem arises when the historical price series are not available for some securities or, when they are available, they are not fully reliable due to the lack of liquidity (Al Janabi, 2008, 2013).

Given that institutional investors usually have longer time horizons, the liquidity of their positions will be lower. The investment horizon of the investor as well as the liquidity characteristics of the mutual fund need to be integrated into the risk quantification process. For instance, portfolios with long investment horizons and/or low liquidity need distinct risk measures than those that have shorter horizons and are very liquid. The choice of the time horizon or number of days to liquidate (unwind) different assets is a very important factor and has a big impact on VaR statistics, as it depends on the objectives of the portfolio, the liquidity of its positions, and the expected holding periods. Typically, for a bank's trading portfolio invested in highly liquid currencies, a one-day horizon may be acceptable. For an investment manager with a monthly re-balancing and reporting focus, a 30-day period may be more appropriate. Ideally, the holding periods should correspond to the longest horizon for orderly portfolio liquidation (Al Janabi, 2008).

Liquidity is a key risk factor, which until lately, has not been appropriately dealt with by market risk models. Illiquid trading positions can add considerably to losses and can give negative signals to traders due to the higher expected returns they entail. Thus, the concept of liquidity trading risk is immensely important for using VaR accurately and the many turmoil in global financial markets confirm the need for laborious treatment and assimilation of liquidity trading risk into VaR models.

The simplest way to account for liquidity trading risk is to extend the holding horizon of illiquid positions to reflect a suitable closeout period. An adjustment can be made by adding a multiplier to the VaR measure of each trading asset type, which in the end depends on the liquidity of each individual security. Nonetheless, the weakness of this method is that it allows for subjective assessment of the liquidation period. Furthermore, the typical assumption of a one-day horizon (or any inflexible time horizon) within the VaR framework, neglects any computation of trading risk related to liquidity effect (i.e. when and whether a trading position can be sold out and at what price). A robust VaR modeling technique should incorporate a liquidity premium (or liquidity risk factor). This can be worked out by devising a modeling algorithm by which one can unwind multiple-asset positions, not at some ad hoc rates, but at the rates that market conditions are optimum, so that one can effectively set risk values for the liquidity effects. In general, this will raise significantly the VaR, or the amount of economic capital cushion to support the trading positions.

In fact, if returns are independent and they can have any elliptical multivariate distribution, then it is possible to convert the VaR horizon parameter from daily to any t-day horizon. The variance of a t-day return should be

t times the variance of a 1-day return or $\sigma^2 = f(t)$. Thus, in terms of standard deviation (or volatility), $\sigma = f(\sqrt{t})$ and the daily or overnight VaR number [VaR (1-day)] can be adjusted for any t-day horizon as:

$$\text{VaR}\ (t\text{-day}) = \text{VaR}\ (1\text{-day})\sqrt{t}$$

The above formula was proposed and used by J.P. Morgan in their earlier RiskMetrics™ method (Morgan Guaranty Trust Company, 1994). This methodology implicitly assumes that liquidation occurs in one block sale at the end of the holding period and that there is one holding period for all assets, regardless of their inherent trading liquidity structure. Unfortunately, the latter approach does not consider real-life trading situations, where traders can liquidate (or re-balance) small portions of their trading portfolios on a daily basis. The assumption of a given holding horizon for orderly liquidation inevitably implies that assets' liquidation occurs during the holding period. Accordingly, scaling the holding period to account for orderly liquidation can be justified if one allows the assets to be liquidated throughout the closeout period.

In this work, we examine a robust modeling algorithm for computing a closed-form parametric L-VaR that can be used for the evaluation of liquidity trading risk and coherent economic capital. The proposed modeling technique and liquidity-scaling factor are more realistic and less conservative than the conventional root-t multiplier. In this research study, the re-engineered modeling techniques and the non-linear robust optimization algorithms are based on the Al Janabi model (Al Janabi, 2008; Madoroba and Kruger, 2014). In essence, the suggested multiplier is a function of a predetermined liquidity threshold(s) defined as the maximum position that can be unwound without disturbing market prices during one trading day. The essence of the modeling algorithm relies on the assumption of a stochastic stationary process and some rules of thumb, which can be of crucial value for more accurate risk assessment during market stress periods when liquidity dries up. To that end, a practical methodology, within a simplified mathematical methodology, is examined below with the goal of incorporating and computing the L-VaR of illiquid assets, detailed along these lines:

The market risk of an illiquid trading position is larger than the risk of an otherwise identical liquid position. This is because unwinding the illiquid position takes longer than unwinding the liquid position, and, as a result, the illiquid position is more exposed to the volatility of the market for a longer period of time. In this modeling technique, an equity trading position will be thought of illiquid if its size surpasses a certain liquidity threshold. The threshold (which is determined by traders for different equities and/or financial markets) and defined as the maximum position which can be unwound, without disrupting market prices, in normal market conditions and during one trading day. Consequently, the size of the equity trading position relative to the threshold plays an important role in determining the number of days that are required to close the entire position. This effect can be translated into a liquidity increment (or an additional liquidity risk factor) that can be incorporated into VaR analysis. If for instance, the par value of an equity position is \$100,000,000 and the liquidity threshold is \$50,000,000, then it will take 2 days to sell out the entire trading position. Therefore, the initial position will be exposed to market variation for 1 day, and the rest of the position (i.e. \$50,000,000) is subject to market variation for an additional day. If it assumed that daily changes in market values follow a stationary stochastic process, the risk exposure due to illiquidity effects is given by the following modeling algorithm:

In order to take into consideration the full illiquidity of equity assets (i.e. the required unwinding period to liquidate an asset) we define the following:

t = number of liquidation days (t-days to liquidate the equity asset fully);

$\sigma_{adj}{}^2$ = conditional variance of the illiquid equity trading position; and

σ_{adj} = liquidity risk factor or the conditional standard deviation of the illiquid equity trading position.

The proposed modeling technique assumes that the trading position is closed out linearly over t-days and, hence, it uses the logical assumption that the losses due to illiquid trading positions over t-days are the sum of losses over the individual trading days. Moreover, we can assume with reasonable accuracy that asset returns and losses due to illiquid trading positions are independent and identically distributed and serially uncorrelated day to day along the closeout horizon and that the conditional variance of losses due to liquidity risk over t-days is the sum of the conditional variances ($\sigma_i{}^2$, for all $i = 1, 2, \ldots, t$) of losses on the actual trading days, thus:

$$\sigma_{adj}{}^2 = \left(\sigma_1{}^2 + \sigma_2{}^2 + \sigma_3{}^2 + \cdots + \sigma_{t-2}{}^2 + \sigma_{t-1}{}^2 + \sigma_t{}^2\right) \tag{5}$$

In fact, the square root-t approach (i.e. equation [4]) is a simplified special case of equation (5) under the assumption that the daily variances of losses throughout the holding period are all the same as first-day variance, $\sigma_1{}^2$, thus $\sigma_{adj}{}^2 = \left(\sigma_1{}^2 + \sigma_1{}^2 + \sigma_1{}^2 + \cdots + \sigma_1{}^2\right) = t\sigma_1{}^2$. As discussed above the square root-t equation overestimates assets liquidity risk since it does not consider that traders can liquidate small portions of their trading portfolios on a daily basis, and then the whole trading position can be sold completely on the last trading day. Indeed, in real financial markets operations, liquidation occurs during the holding period, and thus scaling the holding horizon to account for orderly liquidation can be justified if one allows the multiple-asset to be liquidated throughout the closeout period. As such, for this special linear liquidation case and under the assumption that the conditional variance of losses of the first trading day decreases linearly each day as a function of *t* we can derive from equation (5) the following expression for the conditional variance:

$$\sigma_{adj}{}^2 = \left(\left(\frac{t}{t}\right)^2 \sigma_1{}^2 + \left(\frac{t-1}{t}\right)^2 \sigma_1{}^2 + \left(\frac{t-2}{t}\right)^2 \sigma_1{}^2 + \cdots + \left(\frac{3}{t}\right)^2 \sigma_1{}^2 + \left(\frac{2}{t}\right)^2 \sigma \quad + \quad _t$$

$$\sigma_1{}^2 + \left(\frac{1}{t}\right)^2 \sigma_1{}^2 \right) \tag{6}$$

Evidently, the additional liquidity risk factor depends only on the number of days needed to sell an illiquid equity position linearly. In the general case of *t*-days, the conditional variance of the liquidity risk factor is given by the following expression of *t*:

$$\sigma_{adj}{}^2 = \sigma_1{}^2 \left(\left(\frac{t}{t}\right)^2 + \left(\frac{t-1}{t}\right)^2 + \left(\frac{t-2}{t}\right)^2 + \cdots + \left(\frac{3}{t}\right)^2 + \left(\frac{2}{t}\right)^2 + \left(\frac{1}{t}\right)^2\right) \tag{7}$$

To calculate the sum of the squares, it is convenient to use a short-cut mathematical route. From mathematical finite-series, the following relationship can be obtained:

$$(t)^2 + (t-1)^2 + (t-2)^2 + \cdots + (3)^2 + (2)^2 + (1)^2 = \frac{t(t+1)\,(2t+1)}{6} \tag{8}$$

Hence, after substituting equation (8) into equation (7), the following can be achieved:

$$\sigma_{adj}{}^2 = \sigma_1{}^2 \left[\frac{1}{t^2}\left\{(t)^2 + (t-1)^2 + (t-2)^2 + \cdots + (3)^2 + (2)^2 + (1)^2\right\}\right]$$

$$\text{or } \sigma_{adj}{}^2 = \sigma_1{}^2 \left(\frac{(2t+1)\,(t+1)}{6t}\right) \tag{9}$$

Accordingly, from equation (9) the liquidity risk factor can be expressed in terms of conditional volatility as:

$$\sigma_{adj} = \sigma_1 \left\{\sqrt{\frac{1}{t^2}\left[(t)^2 + (t-1)^2 + (t-2)^2 + \cdots + (3)^2 + (2)^2 + (1)^2\right]}\right\} \text{ o}$$

$$\text{or } \sigma_{adj} = \sigma_1 \left\{\sqrt{\frac{(2t+1)\,(t+1)}{6t}}\right\} \tag{10}$$

The final result of equation (10) is of course a function of time and not the square root of time as typically employed by some market participants based on the RiskMetrics™ methodologies (Morgan Guaranty Trust Company, 1994). The above modeling algorithm can also be used to compute L-VaR for any time horizon. Likewise, in order to perform the computation of L-VaR under illiquid market outlooks, it is possible to use the liquidity risk factor of equation (10) and define the following:

$$L - \mathrm{VaR}_{\mathrm{adj}} = \mathrm{VaR}\sqrt{\frac{(2t+1)\,(t+1)}{6t}} \tag{11}$$

where VaR = value at risk under liquid market conditions, and L-VaR_{adj} = value at risk under illiquid market perspectives. The latter equation indicates that L-VaR_{adj} > VaR, and for the special case when the number of days to liquidate the entire equity assets is one trading day, then we have the equality of L-$\mathrm{VaR}_{\mathrm{adj}}$ = VaR. Thus, the difference between the values of L-$\mathrm{VaR}_{\mathrm{adj}}$–VaR should equal to the residual market risk due to the illiquidity assets under illiquid market settings. As a matter of fact, the number of liquidation days (t) necessary to close out the entire equity assets is related to the choice of the liquidity threshold. However, the size of this threshold is likely to change under adverse market conditions. As such, the choice of the liquidation horizon can be estimated from the total trading position size and the daily trading volume that can be unwound into the market without significantly disrupting equity market prices. In actual practices, it is generally estimated as:

$$t = |\text{total trading position size of asset}_i \,/\, \text{daily trading volume of asset}_i\,|, s.t.\;\; t \geq 1.0 \tag{12}$$

In practice, the daily trading volume of any equity asset is estimated as the average volume over some period of time, generally a month of trading activities. In effect, the daily trading volume of assets can be regarded as the average daily volume or the volume that can be unwound during crisis periods. The trading volume during crisis periods can be roughly approximated as the average daily trading volume less a number of standard deviations. Albeit this alternative approach is quite simple, it is still relatively objective. Moreover, it is reasonably easy to gather the required data to perform the necessary liquidation scenarios.

In essence, the above liquidity-scaling factor (or multiplier) is more realistic and less conservative than the conventional root-t multiplier and can aid financial entities in allocating reasonable economic capital requirements. Furthermore, the above modeling algorithm can be applied for the computation of L-VaR for each trading position and for the entire portfolio of multiple-asset. In order to compute the L-VaR for the whole trading portfolio under illiquid market outlooks ($\text{L-VaR}_{P_{\text{adj}}}$), the above mathematical technique can be extended, with the aid of equation (3), into a matrix-algebra form to yield the following:

$$\text{L-VaR}_{P_{\text{adj}}} = \sqrt{\left[\text{L-VaR}_{\text{adj}}\right]^{T} [\rho] \left[\text{L-VaR}_{\text{adj}}\right]} \tag{13}$$

The above mathematical algorithm (in the form of two vectors and a matrix, i.e. $\left[\text{L-VaR}_{\text{adj}}\right]^{T}$, $\left[\text{L-VaR}_{\text{adj}}\right]$ and $[\,\rho\,]$) can facilitate the programming and machine learning computational processes so that the portfolio and risk managers can designate different liquidation horizons for the whole portfolio and/or for each trading asset according to the number of days required to liquidate the entire assets. The latter can be achieved by specifying an overall benchmark liquidation horizon to unwind the entire constituents of the portfolio. The number of days required to liquidate a position (of course, depending on the type of each asset) can be assessed by means of equation (2), and using the available trading volume data that are published frequently. In addition, it would be advisable to compare the obtained empirical closeout periods with the actual market assessments of the different traders of each trading unit, such that, to reach a consensus on the liquidity horizons to be implemented in the computation of L-VaR. As a result, it is possible to establish simple statistics of the trading volume that can be liquidated and the necessary time horizon to unwind the whole volume[5]. As a matter of fact, our robust liquidity risk factor technique, once compared with earlier liquidity risk models, can lead to even further reductions in the overall risk of the equity trading portfolio; and hence in the amount of regulatory capital and/or economic capital, as specified by Basel II and Basel III capital adequacy requirements.

3.3 Assessment of economic capital with different liquidation horizons and dependence measures (unconditional correlation factors)

The annual economic capital necessary to support trading activities under both illiquid normal and severe illiquid market settings is derived in this chapter. When calculating economic capital cushion, we want to use the same time horizon and confidence level for the risk exposures of all assets. The time horizon is usually one year ahead (assuming 260 active business trading days in the year) and the confidence level is often chosen as 99.97% (or 3.43 quantile) for an AA-rated financial institution. The key assumption behind this method is that the probability distribution of profits and losses (*P&L*) for each day during the next year will be the same as that estimated for the first current trading day and that the distribution of *P&L* is independent. Moreover, financial entities are involved in several large businesses besides the business of taking equity risk. The variety of trading activities provides a diversification benefit that will significantly reduce the risk of firm-wide default from a movement in equity prices. To take the diversification effect into account in our estimation of the contribution of the equity trading unit to firm-wide *P&L*, we multiply the stand-alone value for the conditional liquidity-adjusted volatility by the square root of the correlation between business units ($\sqrt{\rho_{BU}}$). As such, the 99.97% worst-case loss is then 3.43 times the conditional overall portfolio liquidity-adjusted volatility of the one-year profit/loss, or more formally from equations (3) and (13) we can define:

$$\text{Economic capital (EC)} =$$

$$\begin{aligned} &= \left(\frac{\alpha_{EC}}{\alpha}\right)\sqrt{H}\,\sqrt{\rho_{BU}}\,\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\text{L-VaR}_i\ \text{L-VaR}_j\ \rho_{i,j}} \\ &= \left(\frac{\alpha_{EC}}{\alpha}\right)\sqrt{H}\,\sqrt{\rho_{BU}}\,\sqrt{\left[\text{L-VaR}_{\text{adj}}\right]^T\ [\rho]\left[\text{L-VaR}_{\text{adj}}\right]} \end{aligned} \tag{14}$$

where α_{EC} is the economic capital quantile of 3.43, α is the daily VaR quantile as illustrated in equation (1), H is the number of active trading days in the year, ρ_{BU} is the correlation factor required to account for the diversification benefit provided by having the equity trading risk unit as one of a number of diversified financial businesses. Furthermore, $\text{L-VaR}_{P_{\text{adj}}}$ is defined in equation (13), so that:

$$\text{Economic capital (EC)} = \left(\frac{\alpha_{EC}}{\alpha}\right)\sqrt{H}\,\sqrt{\rho_{BU}}\ \text{L-VaR}_{P_{\text{adj}}} \tag{15}$$

The elements of the vectors of equation (14), i.e. $\text{L-VaR}_{i\,\text{adj}}$, for each trading asset can now be computed with the aid of equations (2) and (11) in this manner:

$$\text{L-VaR}_{i\,adj} =$$

$$\left|\alpha \times \sigma_i \times \text{mark-to-market value of asset}_i \times Fx_i \sqrt{\frac{(2t_i+1)\,(t_i+1)}{6t_i}}\right| \tag{16}$$

Now, we can define the ultimate two vectors $\left[\text{L-VaR}_{\text{adj}}\right]^T$ and $\left[\text{L-VaR}_{\text{adj}}\right]$ as follows:

$$\left[\text{L-VaR}_{\text{adj}}\right]^T = \left[\text{L-VaR}_{1_{\text{adj}}}\ \ \text{L-VaR}_{2_{\text{adj}}}\ \ ....\ \ \text{L-VaR}_{n_{\text{adj}}}\right] \tag{17}$$

$$\left[\text{L-VaR}_{\text{adj}}\right]=\begin{bmatrix}\text{L-VaR}_{1_{\text{adj}}}\\ \text{L-VaR}_{2_{\text{adj}}}\\ \ldots\ldots\ldots\ldots\\ \text{L-VaR}_{n_{\text{adj}}}\end{bmatrix} \tag{18}$$

To examine the relationship between the expected returns and volatility of stock market indices, we can implement a conditional volatility method to determine the risk parameters that are needed for the L-VaR's risk engine and thereafter for the estimation of daily market liquidity risk exposures and economic capital requirements. Indeed, the time-varying pattern of stock market volatility has been widely recognized and modeled as a conditional variance within the GARCH-M (1,1) framework, as originally developed by Engle (1982, 1995). Engle (1982) introduced a likelihood ratio test to ARCH effects and a maximum likelihood method to estimate the parameters in the ARCH model. This approach was generalized by Bollerslev (1986) and Engle and Kroner (1995). The following generalized autoregressive conditional heteroskedasticity in mean, GARCH-M (1,1) model, is used for the estimation of expected return and conditional volatility for each of the time series variables:

$$R_{it}=a_i+b_i\sigma_{it}+\varepsilon_{it}, \tag{19}$$

$$\sigma_{it}^2=c_i+\beta_{i1}\sigma_{it-1}^2+\beta_{i2}\varepsilon_{it-1}^2, \tag{20}$$

where R_{it} is the continuous compounding return of time series i, σ_{it} is the conditional standard deviation as a measure of volatility, and ε_{it} is the error term return for time series i. The denotations a_i, b_i, c_i, β_{i1}, and β_{i2} represent parameters to be estimated. The parameters representing variance are assumed to undertake a positive value. In addition, to test for the non-normality (i.e. asymmetrical distribution) in the assets returns, we can use the Jarque–Bera (*JB*) test. The *JB* statistic is computed in this manner:

$$JB=n/6\left\lfloor S^2+(K-3)^2/4\right\rfloor\approx\chi^2(2) \tag{21}$$

where S is the skewness, K is the kurtosis, and n is the number of observations. The JB statistic reassembles an approximately a Chi-squared distribution $[\chi^2(2)]$ with two degrees of freedom. The 95% and 99% percentage points of the Chi-squared distribution with two degrees of freedom are 5.99 and 9.21, respectively, thus, the lower the JB statistic, the more likely distribution is normal.

Essentially, our modeling technique is a robust enhancement and a key improvement to the classical Markowitz (1959) mean-variance method, where the original risk measure, variance, is replaced by L-VaR and economic capital optimization algorithms. The task is attained here by minimizing the economic capital's objective function while requiring a minimum expected return subject to applying several meaningful financial and operational constraints. Thus, by considering different vectors of expected returns and L-VaRs, we can generate efficient and coherent economic capital frontiers. Alternatively, we can also maximize expected returns while not allowing for large risks. For the purpose of this study, the optimization problem is structured as follows:

It is possible to compute from equation (14) the minimum amount of optimum economic capital, necessary to serve as a cushion to support the current trading operation, by solving for the following non-linear quadratic objective function[6]:

$$\text{Minimize : Economic Capital (EC)} =$$

$$\left(\frac{\alpha_{EC}}{\alpha}\right)\sqrt{H}\,\sqrt{\rho_{BU}}\,\sqrt{\left[\text{L-VaR}_{\text{adj}}\right]^{T}\,[\rho]\left[\text{L-VaR}_{\text{adj}}\right]} \tag{22}$$

Subject to the following operational and financial budget constraints as specified by the portfolio and risk managers:

$$\sum_{i=1}^{n} R_i x_i = R_P \;;\; l_i \le x_i \le u_i \quad i = 1,2,\ldots.,n \tag{23}$$

$$\sum_{i=1}^{n} x_i = 1.0 \;;\; l_i \le x_i \le u_i \quad i = 1,2,\ldots., n \tag{24}$$

$$\sum_{i=1}^{n} V_i = V_P \quad i = 1,2,\ldots., n \tag{25}$$

$$[\text{LHF}] \ge 1.0 \;;\; \forall_i \quad i = 1,2,\ldots.., n \tag{26}$$

Here R_P and V_P denote the target portfolio mean expected return and total portfolio volume respectively, and x_i is the weight or percentage asset allocation for each asset. The values l_i and u_i, $i = 1, 2,\ldots, n,$ denote the lower and upper constraints for the portfolio weights x_i. If we choose $l_i = 0$, $i = 1, 2,\ldots, n$, then we have a situation where no short sales are allowed. Moreover, [LHF] indicates an ($n \times 1$) vector of the individual closeout horizon of each asset for all $i = 1, 2,\ldots, n$. Where LHF_i is defined, with the aid of equation (11), for each trading asset in this way:

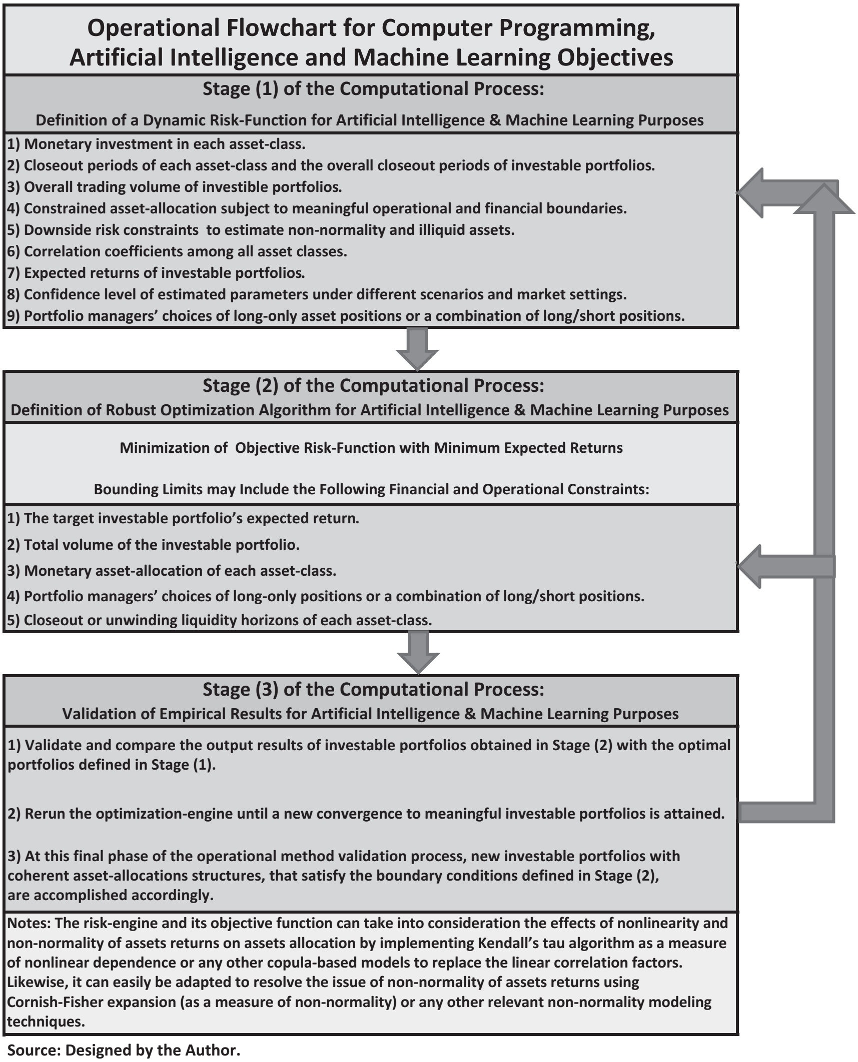

Figure 7.1 Stages of computational processing.
Source: Designed by the author.

$$\text{LHF}_i = \sqrt{\frac{(2t_i + 1)\,(t_i + 1)}{6t_i}} \geq 1.0\ ;\forall_i \quad i = 1,2,\ldots.., n \tag{27}$$

Now the portfolio manager can specify different liquidity horizons and dependence measures and compute the necessary amount of annual economic capital to sustain the trading operation of the financial corporation without subjecting the entity to insolvency matters. The rationality behind imposing the above constraints is to comply with current regulations that enforce capital requirements on investment companies, proportional to their L-VaR and economic capital, besides other operational limits (for instance, the overall volume trading limits).

Set against this background and to maximize its utility as a risk management and portfolio selection method, we have constructed the portfolio management tool such that the proposed risk engine and robust scenario optimization algorithms can be used for computer programming and artificial intelligence and machine learning objectives, machine learning for the policymaking process, and machine learning techniques for the IoT data analytics. To that end, the below graphical flowchart shows a concise outline of the operational stages of the modeling algorithms and their interrelationships for computer programming and artificial intelligence and machine learning objectives, machine learning for the policymaking process, and machine learning techniques for IoT data analytics (Figure 7.1).

4 Conclusion

Modern portfolio theory aims to allocate assets by maximizing the expected risk premium per unit of risk. In a mean-variance framework (Markowitz, 1959), the risk is defined in terms of the possible variation of expected portfolio returns. The focus on standard deviation as the appropriate measure for risk implies that investors weigh the probability of negative returns equally against positive returns. The choice therefore of mean-variance efficient portfolios is likely to give rise to an inefficient strategy for optimizing expected returns for financial assets whilst minimizing risk.

Given the fact that mean-variance optimizers have serious financial deficiencies, which could often lead to financially meaningless "optimum" portfolios (Michaud, 1989; Fabozzi et al., 2006), in this chapter we examine how to model coherent economic capital portfolio choices for an equity portfolio manager under the assumption of different liquidation horizons and by implementing different long-only trading scenarios or a combination of long- and short-sale trading strategies. In this chapter, we examine an optimum and coherent economic capital portfolio selection model that implements a downside risk constraint rather than standard deviation alone.

In our modeling technique, the downside risk is written in terms of portfolio L-VaR, so that additional risk resulting from any non-normality and illiquid assets may be used to compute the portfolio L-VaR and economic capital. This enables a much more generalized framework to be developed, with the distributional assumption most appropriate to the type of financial assets to be employed. We then provide a robust portfolio optimization algorithm using L-VaR as a risk measure subject to the application of meaningful financial and operational constraints. To that end, in this research study, the modeling techniques and the non-linear robust optimization algorithms are based on the Al Janabi model (Al Janabi, 2008; Madoroba and Kruger, 2014) and can have important uses and applications in machine learning and artificial intelligence, machine learning for the policymaking process, the IoT, and machine learning techniques for IoT data analytics.

This chapter extends previous approaches to optimization problems with L-VaR constraints. In particular, the modeling algorithm can be used for minimizing L-VaR under several budget constraints and ultimately for determining the amount of economic capital necessary to sustain financial operation without subjecting the trading unit to violation of capital adequacy. Furthermore, multiple L-VaR constraints with various unwinding periods and correlation factors can be used to shape the profit-loss distributions. In some cases, the mean-variance optimizations are highly unstable, that is, small changes in the input assumptions can lead to large changes in the solutions (Michaud, 1989; Fabozzi et al., 2006). As such, in this work, the optimization algorithm is designed by finding a set of portfolios that minimize economic capital subject to given expected returns, trading volumes, and liquidity horizons. To that end, the economic capital objective function is constrained by a downside risk measure in addition to several financial and operational constraints, such as total volume, long- and short-sale trading assets, asset allocation weights, and closeout periods. Our model is a robust enhancement and a key improvement to the classical Markowitz (1959) mean-variance method, where the original risk measure, variance, is replaced by L-VaR and economic capital algorithms and by guaranteeing minimum expected return under different liquidation horizons. This modeling algorithm can aid in solving some of the real-world trading dilemmas under adverse market conditions: when liquidity dries up; correlation factors switch signs; and the incorporation of the non-normal distribution of assets returns in the risk measurement process.

The modeling algorithms are interesting in terms of theory as well as for key practical applications and can have many uses and applications in financial markets, particularly in light of the 2007–2009 global financial meltdown. In addition, the proposed optimization techniques and risk assessment algorithms can aid in advancing quantitative risk management practices in emerging and developed markets, particularly in light of the 2007–2009 financial turmoil. In addition, the proposed computational techniques can have key uses and applications in machine learning and artificial intelligence, machine learning for the policymaking process, expert systems, smart financial functions, the IoT, and FinTech in big data environments. Furthermore, it provides key real-world applications for portfolio and risk managers, treasury directors, risk management executives, policymakers, and financial regulators to comply with the requirements of Basel III practices on liquid risk and capital adequacy.

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Notes

1 For some of latest literature on machine learning, machine learning for the policymaking process and expert systems in finance for modern portfolio optimization and regulatory risk management, we refer the readers to Kalayci et al. (2019), Ban et al. (2018), Al Janabi (2019), and Paiva et al. (2019).

2 For other relevant literature on liquidity risk, asset pricing, internal risk models, and portfolio choice and diversification one can refer as well to Al Janabi (2021a,b,c), Asadi and Al Janabi (2020), Arreola-Hernandez and Al Janabi (2020), Ruozi and Ferrari (2013), Grillini et al. (2019), Roch and Soner (2013), Al Janabi, Ferrer, and Shahzad (2019), Angelidis and Benos (2006), Berkowitz (2000), Madhavan et al. (1997), Hisata and Yamai (2000), Amihud et al. (2005), Takahashi and Alexander (2002), Arreola-Hernández, et al. (2017), Arreola-Hernandez, et al. (2015), Cochrane (2005), and Meucci (2009), among others. Furthermore, within the copula technique, and particularly the vine copula approach, there were indeed very few studies in this respect and most of published research is still focused on the issue of transaction costs (i.e., bid-ask spreads). In particular, Weiß and Supper (2013) investigate the issue of forecasting liquidity-adjusted intraday VaR with vine copulas. In their paper, they propose to model the joint distribution of bid-ask spreads and log returns of a stock portfolio by implementing Autoregressive Conditional Double Poisson and GARCH processes for the marginals and vine copulas for the dependence structure. By estimating the joint multivariate distribution of both returns and bid-ask spreads from intraday data, they incorporate the measurement of commonalities in liquidity and co-movements of stocks and bid-ask spreads into the forecasting of three types of liquidity-adjusted intraday VaR.

3 The mathematical approach, modeling algorithms, and robust optimization techniques presented herein are largely drawn from Al Janabi (2012, 2013 and 2014), and Al Janabi et al. (2017) research papers.

4 The dependence measure function can take different forms. For liner dependence, it can be represented by the typical Pearson's correlation coefficients. However, for nonlinear and non-normal distributions, Kendall's tau and other forms of copulas functions can be used to replace the dependence measure function.

5 In fact, the concept of liquidity risk in financial markets and institutions can imply either the added transaction costs related to trading large quantities of a certain financial security, or it can deal with the ability to trade this financial

asset without triggering significant changes in its market prices (see, Roch and Soner (2013) for further details and empirical analysis.

6 The risk-engine and its objective function can take into consideration the effects of nonlinearity and non-normality of assets returns on assets allocation by implementing Kendal's tau algorithm as a measure of nonlinear dependence or any other copula-based models to replace the linear correlation factors. Likewise, it can easily be adapted to resolve the issue of non-normality of assets returns using Cornish-Fisher expansion (as a measure of non-normality) or any other relevant non-normality modeling techniques.

8 Random Forest and Grey Methodology in Dynamic Portfolio Selection

Tihana Škrinjarić and Silvija Vlah Jerić

1 Introduction

Today, the process of portfolio selection represents a very complicated task for the (potential) investor. This is due to the different knowledge the investor has to have and obtain (regarding finance theory and quantitative models and methods), the quantity of information and data which has to be observed and processed on a daily basis, and the overall dynamics present on financial markets, new methodologies being developed, and computational possibilities today (Škrinjarić, 2020). One part of academic research focuses on mathematical tools in order to facilitate the decision-making process of the dynamic portfolio selection. Thus, it is not surprising that the number of papers that develop and implement different approaches in the finance area is constantly growing. Previous research found that machine learning (ML henceforward) tools improve the prediction process of expected return behavior (Weigand, 2019) when compared to traditional forecasting methods (e.g. typical models and methods within econometrics, such as ARMA and GARCH models, autoregressive moving average, and conditional autoregressive conditional heteroskedasticity). Since there do not exist any obstacles in terms of computing resources and data availability (Arnott et al., 2018), there are almost no limits to employ different ML tools. Often, the idea is to obtain a set of comprehensive rules (Vlah Jerić, 2020b) that the decision-maker can understand and implement in different ways.

The application of general ML approaches within portfolio management is growing extremely fast in the last couple of years. Researchers apply some of the techniques, models, and ML methods, or more often, their combinations or combinations with other approaches from econometrics or operations research. Thus, this section gives a brief overview of related research, as a detailed classification of relevant research is not the main topic of this chapter. For papers on the literature review, please refer to Weigand (2019) or Gu et al. (2020) as some examples. Some authors focus on the identification of best predictors of future price movements (Harvey and Liu, 2016); others extend the existing approaches such as the factor models within asset pricing via instrumented principal component analysis

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as in Kelly et al. (2017). Tree-based models within the cross-section stock return analysis are applied in Moritz and Zimmermann (2016). Manojlović and Štajduhar (2015) used random forest (RF) for predicting stock market trends on Zagreb Stock Exchange (ZSE). Vlah Jerić (2021) compared the performance of five different ML algorithms on the classification of trading days into favorable and non-favorable days on Croatian stock index data on resamples. Similar research by Vlah Jerić (2020a), as an extension, compared those algorithms to new data by using the optimal model obtained by tuning the algorithms. The results revealed significant differences between the algorithms in general and indicated that RF seems to be a promising algorithm of choice for that type of problems.

However, there still exist gaps in the literature. We will fill one of those gaps by combining an ML approach to RF with a relatively new methodological approach of grey system theory (GST; Liu and Lin, 2006, 2010; Kuo et al., 2008). This methodology is being developed since the 1980s and focuses on uncertain data, i.e. the term grey refers to data that has uncertainties and incompleteness. GST consists of different models and methods which complement existing approaches within operational research, econometrics, and general approaches to financial modeling. As the RF algorithm will be used for stock price prediction, the GST approach will consist of the grey relational analysis (GRA) approach, which is a methodological approach of constructing a ranking system between alternatives. In that way, the decision-making process is facilitated. Some of the applications of the GRA can be found in Škrinjarić and Škrinjarić and Šego (2019). However, as mentioned, a gap in the literature exists in the following way. A combination of ML methods in stock price prediction, and using the predicted values to rank stocks via the GRA approach, and simulating investing strategies based on such approaches is missing. Due to the many benefits of ML and GRA methodologies, the basic idea of this chapter is to popularize them in the ways they will be applied here. Thus, the historical data will be used in the ML part of the modeling to obtain the behavior of stock prices and predict it in the future. Based on the predictions, the GRA approach is then used to rank the stocks for the dynamic portfolio selection. Another contribution of this chapter is that the criteria used for the ranking system are based on the investor's utility theory and not random variables.

The rest of the chapter is structured as follows. In the second section, we give an overview of the methodologies used in the empirical part of the chapter, which is the third section. The discussion and conclusion are given in the fourth section.

2 Methodology Description

2.1 Random Forest

RF is an ML algorithm that can be used for classification and regression problems. The basic idea of RF is the construction of a forest of trees (a large number of decision trees) using random inputs (Ho, 1998; Breiman, 2001). The output of the algorithm is basically derived as a consensus output of those trees (the most common output).

RF algorithm is often tuned, before being used on test data, in order to find the optimal model by varying its parameters. For example, a type of cross-validation can be performed on training data in order to find a number of randomly selected predictors, i.e. the number of variables randomly sampled as candidates at each split. However, in this work, this is not done since the idea was to keep it as simple as possible and just try to use the setup suggested in the literature and implemented as default in the *randomForest* package (Liaw and Wiener, 2002) in *R* (R Core Team, 2020). Thus, the number of variables randomly sampled in each split is set at max (floor(ncol(x) / 3), 1), where ncol(x) is the number of predictors.

In this chapter, RF is used for regression, i.e. for forecasting stock market index value based on its previous values (including also high and low values, as well as returns) and selected technical indices. The technical indices used are the same as were used in the research by Vlah Jerić (2021, 2020a,b). The description of calculations of those indicators is omitted here since they are done exactly as suggested by Bruni et al. (2016). The calculations include choosing certain parameters and those were set at values often used as defaults by traders and scientists in intraday trading. The indicators used are the following:

- Momentum over five periods (MOM),
- Exponential moving average (EMA) over 12 and 26 periods (EMA12 and EMA26, respectively),
- Moving average convergence/divergence with 12, 26, and 9 time periods (respectively) selected as three parameters needed for calculation (MACD),
- Return on investment (ROI) over 10, 20, and 30 periods (ROI10, ROI20, and ROI30, respectively),
- Relative strength index (RSI) over 10, 14, and 30 periods (RSI10, RSI14, and RSI30, respectively),
- Stochastic relative strength index (SRSI) over 10, 14, and 30 periods (SRSI10, SRSI14, and SRSI30, respectively),
- Average true range over 14 periods (ATR),
- Average directional index over the last 14 periods (ADX),
- Williams %R over 14 periods (WPR),
- Commodity channel index over 20 periods (CCI), and
- Ultimate oscillator with 7, 14, and 28 time periods (respectively) selected as three parameters needed for calculation (UO).

2.2 Grey Relational Analysis

As mentioned in the introduction, the GRA approach is a part of the GST. Here, we follow Liu et al. (2016) and Liu and Lin (2006, 2010) in the description of basic relations and notations. As the investor is the potential decision-maker in this research, it is supposed that he has data on J behavioral sequences on N alternatives which are being ranked. The sequences are the expected return, standard deviation, coefficient of skewness, and coefficient of kurtosis of a return distribution, and the alternatives are the stock market indices. Each sequence is denoted with $j \in \{1, 2,..., K\}$, and the stock index is denoted with $n \in \{1, 2,..., N\}$. Now, all of the data can be written in a matrix form for every week of the analysis as:

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \dots & x_1(J) \\ x_2(1) & x_2(2) & & x_2(J) \\ \dots & & \dots & \\ x_N(1) & x_N(2) & \dots & x_N(J) \end{bmatrix}, \tag{1}$$

in which each row refers to the nth alternative and each column refers to the criterion (sequence) j. For example, the $(x_n(1), x_n(2),..., x_n(J))$ is the behavioral sequence of the nth alternative. In our analysis, $J = 4$, due to four moments of the return distribution. The rationale for using the first four moments is as follows. Investors make their decisions via the von Neumann–Morgenstern utility function which ranks alternatives based on preferring greater expected return and skewness on one side, and investor prefers smaller even moments of return distributions (standard deviation and kurtosis), as in Arditti (1967), Müller and Machina (1987), Jurczenko and Maillet (2005), Jondeau and Rickinger (2006).

In the next step, the normalization of the data is performed, so that the data in (1) can be comparable. As investor wants the odd moments of the return distribution to be the greatest possible, these sequences are normalized as follows:

$$y_n(j) = \frac{x_m(j) - \min\limits_m x_m(j)}{\max\limits_n x_n(j) - \min\limits_n x_n(j)}. \tag{2}$$

The even moments are normalized in the following way:

$$y_n(j) = \frac{\max\limits_n x_n(j) - x_n(j)}{\max\limits_n x_n(j) - \min\limits_n x_n(j)}. \tag{3}$$

Now, the normalized data are compared to an optimal value, called the referent sequence $y^*(j)$ for every criterion j. This could be a value that the investor can set; it could be based on previous empirical research, etc. Usually, the literature uses the value of 1 for every criterion, as the normalizations in (1) and (2) set all of the values to be between 0 and 1, with 1 being the best value. A detailed discussion can be found in Kuo et al. (2008). The third step is to calculate the differences between every value in (2) or (3) and the $y^*(j) = 1$:

$$\Delta y_n(j) = 1 - y_n(j). \tag{4}$$

The fourth step is to calculate the grey relational coefficient (GRC):

$$G_n(j) = \frac{\Delta_{\min} + p\Delta_{\max}}{\Delta y_n(j) + p\Delta_{\min}}, \tag{5}$$

where p is the distinguishing coefficient, $p \in [0,1]$, $\Delta_{\min} = \min\{\Delta y_1(j), ..., \Delta y_N(j)\}\ \forall j$ and $\Delta_{\max} = \max\{\Delta y_1(j), ..., \Delta y_N(j)\}\ \forall j$. And finally, the grey relational grade (GRG) is the weighted average of all GRG-s for every stock index in every period:

$$\text{GRD}_n = \sum_{j=1}^{J} w_j G_n(j)\ \forall n. \tag{6}$$

The weights w_j can be defined in a number of ways. It only has to hold that $\sum_{j=1}^{J} w_j = 1$. Values in (6) are used to rank the different alternatives, as they represent the degree of similarity between every alternative n and the best referent sequence. Thus, values in (6) will be constructed for every stock market index in every period t so that the portfolio can be formed based on the best performers.

3 Empirical Results

3.1 Data Description

For the purpose of the empirical analysis, we have collected the daily index data on selected stock market indices from Investing (2020). The starting date is May 18, 2015, and the ending date is December 4, 2020. The training period for the RF part starts on May 18, 2015. The GRA evaluation part and the simulation of the trading strategies range from March 23, 2020, until December 4, 2020. Included stock market indices are S&P 500 (USA), FTSE 350 (UK), ATX (Austria), BSE SOFIX (Bulgaria), PX (Czechia), CAC All shares (France), and MOEX (Russia). These are included due to data (un) availability of these and other indices, as well as the option of international diversification possibilities.

Table 8.1 Descriptive statistics for indices and return series

Index	*ATX*	*BSE*	*PX*	*CAC*	*MOEX*	*FTSE*	*S&P*
Mean	2785.494	552.4491	993.1361	6045.187	2282.947	3840.391	2602.290
Median	2880.045	570.6700	1008.040	6165.780	2254.780	3942.650	2639.400
Max	3688.780	730.9000	1142.950	7412.580	3219.920	4381.120	3702.250
Min	1630.840	405.8000	690.3700	4538.050	1584.920	2766.230	1829.080
N	1392	1383	1395	1427	1406	1411	1403
Returns	*ATX*	*BSE*	*PX*	*CAC*	*MOEX*	*FTSE*	*S&P*
Mean	$9.79 \cdot 10^{-5}$	$-3.70 \cdot 10^{-5}$	$-2.38 \cdot 10^{-6}$	0.000143	0.000550	$3.49 \cdot 10^{-5}$	0.000395
Median	0.000401	0.000000	0.000444	0.000593	0.000568	0.000426	0.000672
Max	0.102055	0.039534	0.073692	0.079407	0.074349	0.085673	0.089683
Min	−0.14675	−0.10811	−0.08161	−0.12421	−0.08713	−0.11214	−0.12765
Std. Dev.	0.014104	0.007569	0.009774	0.012054	0.010600	0.010871	0.012093
Skew	−1.2708	−3.14821	−1.11057	−1.12532	−0.65626	−1.02515	−1.13155
Kurt	20.35115	47.12939	16.12641	16.74688	13.64529	17.70528	23.98929
N	1343	1334	1352	1409	1364	1379	1353

Source: Authors' calculation.

Basic descriptive statistics of index values and their returns over the entire observed period are given in Table 8.1. The returns have been calculated based on the natural logarithm formula: $r_t = \ln(p_t/p_{t-1})$, where r_t is the return series and p_t is the value of the stock market index on day t. As can be seen in Table 8.1, the indices have a wide range of values, with the return series showing variability in the data. Overall, the ATX series was the riskiest when observing the standard deviation of the return series. The COVID-19 crisis is seen in Figure 8.1 in all indices, and it surely has affected the return series to be very negatively skewed (all of the series have negative skewness!). As some indices have greater values compared to others, all of the indices were normalized so that in Figure 8.2 the dynamics could be more visible. Moreover, the correlations between indices are also visible, especially during the bear markets, which are not favorable for portfolio diversification. That is why it is very important to conduct proper quantitative analysis for dynamic financial modeling and portfolio management overall.

3.2 RF Forecasts

The index values forecasts are calculated by using historical values and selected technical indicators as inputs, as described in the previous section. The summary statistics for the inputs are not given here, due to the lack of space for rather extensive tables which would be required to do so (they are

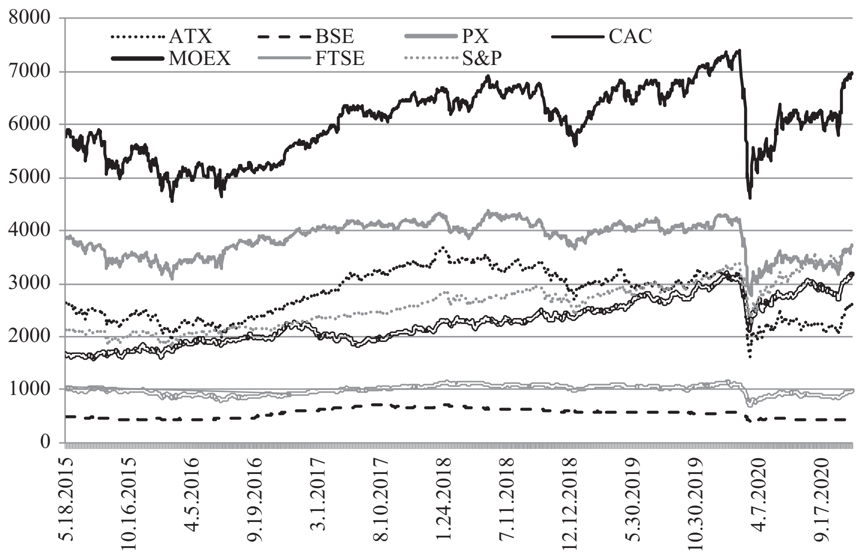

Figure 8.1 Indices observed in the study.
Source: Authors' calculation.

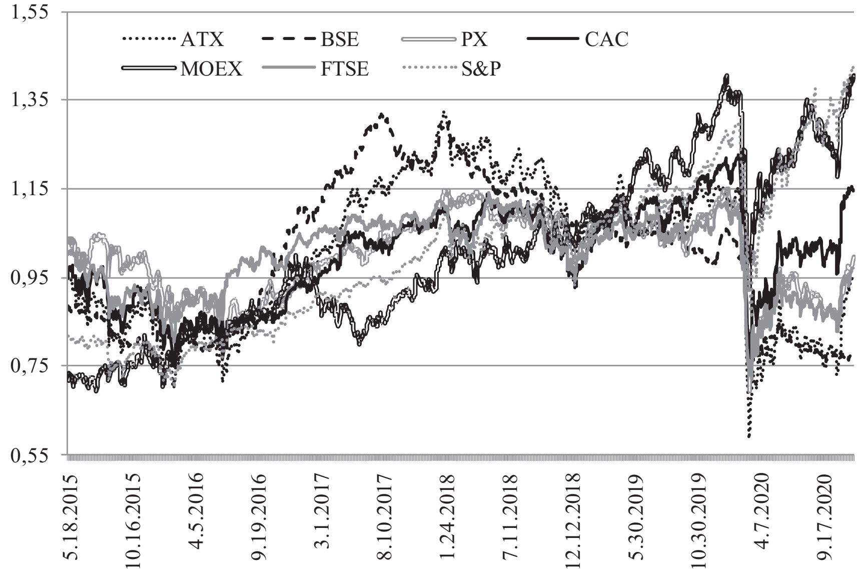

Figure 8.2 Normalized indices observed in the study.
Source: Authors' calculation.

Table 8.2 Descriptive statistics for indices and return series

Index	*ATX*	*BSE*	*PX*	*CAC*	*MOEX*	*FTSE*	*S&P*
RMSE	43.600	3.321	11.642	105.558	39.450	54.713	52.665
Normalized RMSE	0.060	0.067	0.053	0.055	0.049	0.074	0.042
R^2	0.915	0.928	0.934	0.942	0.954	0.868	0.973
Adjusted R^2	0.902	0.917	0.924	0.933	0.947	0.848	0.969

Source: Authors' calculation.

available upon request). Instead, the focus is on the outputs, i.e. the result and the quality of forecasts.

Table 8.2 presents the quality of forecasts for each index made by RF and gives insights into algorithms' performance by showing root mean squared error (RMSE), normalized RMSE, coefficient of determination, and adjusted (adjusted, as usual, for the number of predictors in the model). For the first two measures, lower values are preferred, while for the second two, higher values are preferred. Normalized RMSE is shown since the values of different indices differ substantially and normalization allows comparison between datasets with different scales, i.e. the performance on different indices. To obtain the normalized values, RMSE was divided by the difference between the maximum index value and the minimum index value in the test data.

Results from Table 8.2 show that the RF was the best at forecasting S&P values, while the FTSE performed the worst, in the period that the test set spreads through. Also, it appears that even simply using fixed setup RF for forecasting indices yielded relatively good forecasts. Of course, the algorithm can be tuned for optimal performance, but the idea here was to see how the simple setup behaved. Thus, more refinement of the selection of the inputs as well as tuning the RF will be left for future work.

3.3 GRA Rankings and Trading Strategies Simulation

Based on the previous subsection results, the forecasted values of each index for the next day were used to calculate the estimated return series on a daily basis. In order to construct other moments of the return distribution, the weekly mean return was estimated for each country index, as well as the standard deviation and coefficients of skewness and kurtosis. These estimations were done for the subsample from March 23 to December 4, 2020. Each week, the country indices were ranked via the GRA approach, where the return and skewness series were opted to be the greatest possible and the risk and kurtosis series were opted to be the lowest possible for a country. Finally, the GRG degree was calculated as an average of the individual values for each criterion for every week, so that the decision-making process can be as objective as possible. Thus, market indices that were the best performers on average were ranked better than others.

Several trading strategies were formed:

1. First benchmark strategy, in which the investor holds all seven indices in his portfolio, with equal weights, named: equal. This is a portfolio in which the investor does not need to do any analysis, he doesn't need to follow the market, i.e. it is a passive one. It is diversified in terms that investor holds indices from different countries.
2. The second benchmark strategy is the one in which the Markowitz (1952, 1959) portfolio is constructed by minimizing the weekly portfolio variance. Thus, every week, the investor rebalances his portfolio accordingly.
3. Based on equal weights to all criteria in (6), only one best stock is selected in the portfolio every week, named 1 best.
4. Based on equal weights to all criteria in (6), three best stocks are selected in the portfolio every week, named 3 best.
5. As many investors are risk-averse, greater weight was given to the standard deviation of a return distribution in (6), indices were re-ranked and only one best stock was selected in the portfolio every week, named 1 best_risk.

6 Again, greater weight was given to the standard deviation of a return distribution in (6), indices were re-ranked and three best stocks were selected in the portfolio every week, named 3 best_risk.

It is assumed that the investor starts with a unit value in every strategy. The simulated values are shown in Figure 8.3. It is visible that the best-performing strategy was the 1 best stock one. The worst one was the minimal variance portfolio. However, these findings are not surprising, as the minimal variance portfolio aims to minimize the risk. On the other side, the diversification is better in the minimal variance portfolio, compared to only one index. Moreover, the investor is interested in other performance measures, such as portfolio risk. That is why we have calculated the portfolio standard deviations for every week, and they are shown in Figure 8.4. Although the minimal variance portfolio has overall good performance compared to others, there are some instances in which the 3 best _risk portfolio has lower risk compared to the Markowitz approach. This is due to giving greater weights in the ranking system of the grey approach, which has included the least risky stocks in the portfolio itself. The COVID-19 problems at the beginning of the year are also visible, due to March still being a very volatile month. Overall, our strategies show relatively low volatilities over time.

Afterward, the standardized returns have been calculated, by dividing the portfolio weekly return by the standard deviation. In that way, we obtained the value of how much is the investor rewarded for bearing one unit value of risk. This is depicted in Figure 8.5. It is visible that the majority of our strategies have positive rewards overall, compared to the equally weighted portfolio (second benchmark one), which was the worst-performing one in this

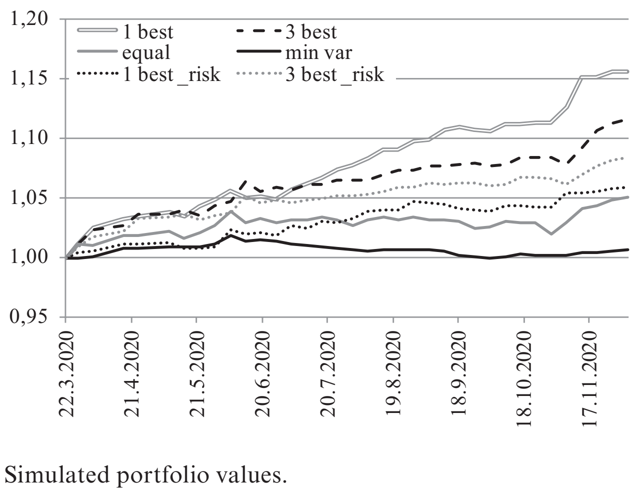

Figure 8.3 Simulated portfolio values.
Source: Authors' calculation.

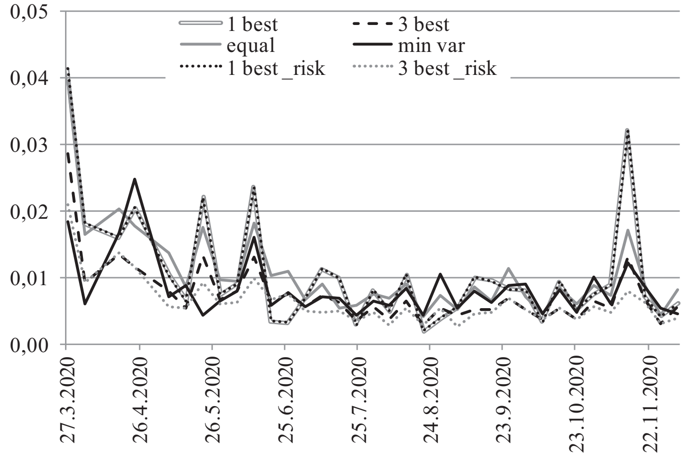

Figure 8.4 Simulated portfolio risks.
Source: Authors' calculation.

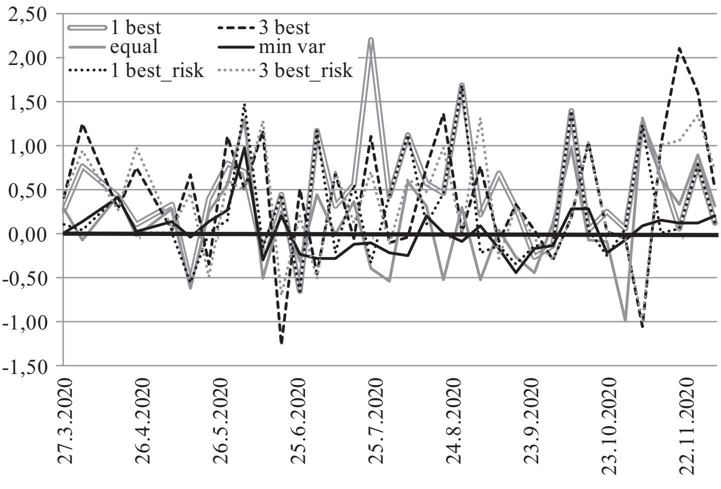

Figure 8.5 Normalized return series (via risk).
Source: Authors' calculation.

case. Furthermore, the COVID-19 problems at the beginning of the sample are not visible here at all, due to the positive returns our strategies obtained. This indicates that such approaches of combining RF with GRA could be very helpful in dynamic portfolio selection.

Finally, several performance measures have been calculated for the analyzed sample. The main results are shown in Table 8.3. Based on the weekly characteristics of each portfolio, mean values have been calculated as follows: average is the average return of each portfolio, Total is the total return at the end of the observed period; SD is the average portfolio standard deviation. Lower SD is the lower partial moment measured as the lower standard deviation. It measures the average dispersion of return series which were lower than the average value (i.e. average deviation of below-average returns). This is a better measure of risk, as it observes those return series that are below-average returns, as the investors do not observe those returns the same they observe the above-average returns (see Chen, 2016 for details). Next, the CE (Certainty Equivalent) was calculated via the formula $CE \approx E(\mu) - 0.5\gamma\sigma^2$, where $E(\mu)$ is the mean return of the portfolio in each week, γ is the coefficient of absolute aversion toward risk and $\sigma2$ is the portfolio risk, i.e. variance. CE tells us how much utility the investor obtains from each portfolio which is equal to the utility he would obtain if he participated in an uncertain gamble (see Cvitanić and Zapatero, 2004). R/Risk is the average return over one unit value of the risk series. Finally, the divers is the diversification measure, i.e. the DI (diversification index), as defined in Woerheide and Persson (1993): $\text{DI} = 1 - \sum_{i=1}^{N} w_i^2$, where w_i is the weight of country i in the portfolio.

Out of nine measures, the 1 best portfolio is outperforming others in six measures in total (bolded values in each row). However, the investor is interested in the risk series and the diversification as well, and here this portfolio is not the best performer. The results could be analyzed from different points of view, i.e. different aversions toward risk. Thus, some investors could be interested in the strategy of investing in only one best-performing index.

Finally, we have compared the portfolio structure of the 1 best portfolio and the minimum variance one to see how much the structure differs. Figures 8.6 and 8.7 are depicting the portfolio structure, and it can be seen that by implementing the strategy of 1 best index, the structure is very

Table 8.3 Descriptive statistics for indices and return series

Measure	*1 best*	*3 best*	*Equal*	*Min Var*	*1 best_risk*	*3 best_risk*
Average	**0.0041**	0.0031	0.0014	0.0002	0.0016	0.0023
Total	**0.1450**	0.1092	0.0491	0.0062	0.0573	0.0809
SD	0.0104	0.0073	0.0104	0.0083	0.0104	**0.0062**
Lower SD	0.0035	0.0044	0.0034	**0.0004**	0.0022	0.0032
CE 1	**0.0041**	0.0031	0.0013	0.0001	0.0015	0.0023
CE 5	**0.0037**	0.0029	0.0010	0.0000	0.0012	0.0022
CE 15	**0.0028**	0.0026	0.0003	−0.0005	0.0003	0.0019
R/Risk	**0.4773**	0.4126	0.1291	0.0169	0.2493	0.3644
Divers	0.000	0.667	0.275	**0.857**	0.000	0.667

Note: Bold values represent significance at 5% p value.
Source: Authors' calculation.

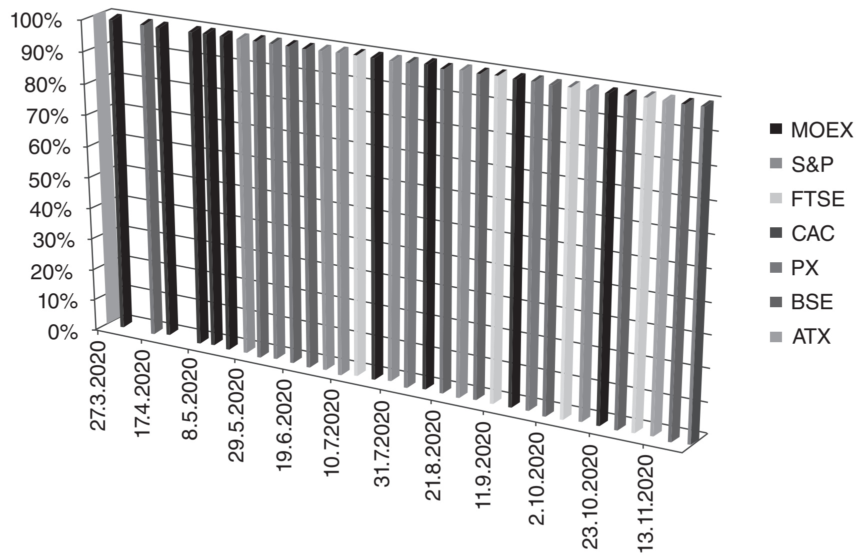

Figure 8.6 Portfolio structure, 1 best index.
Source: Authors' calculation.

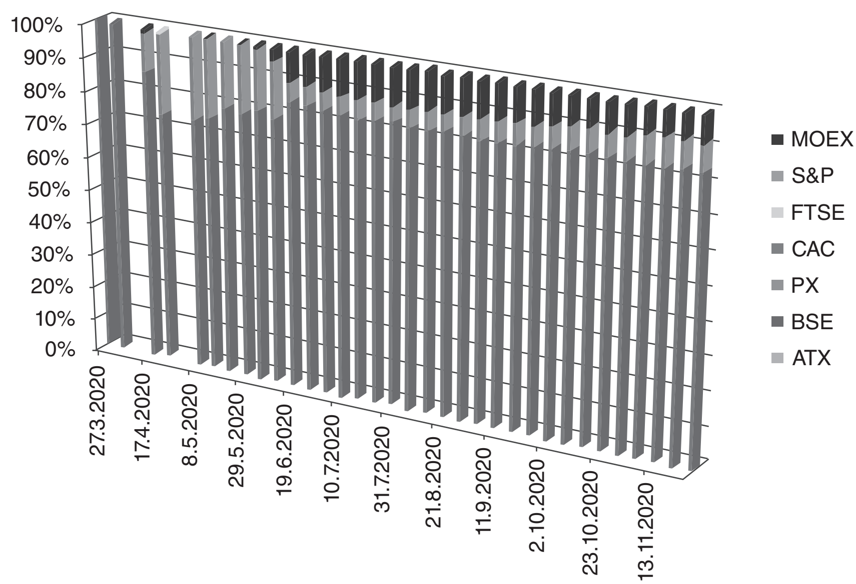

Figure 8.7 Portfolio structure, min var portfolio.
Source: Authors' calculation.

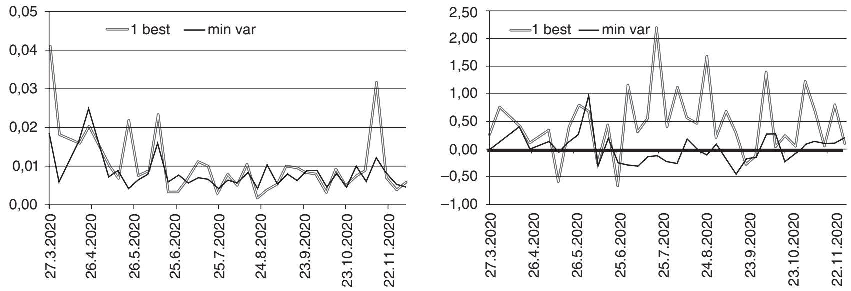

Figure 8.8 Portfolio risk (left panel), standardized return (right panel)
Source: Authors' calculation.

different compared to the min var portfolio, in which the BSE index is the most prominent majority of the time. The BSE index has a majority of the structure in Figure 8.7, due to having the lowest risk and being less correlated to other indices in the observed period. The last figure, Figure 8.8 depicts the risks (left panel) of both portfolios, as well as the return over one unit of risk (right panel). Although the volatility for the 1 best portfolio is greater compared to the min var one, the majority of the standardized returns were positive and greater than the min var portfolio. This ensured the investor to obtain good portfolio value results, a much better-valued portfolio for bearing one unit of risk.

The analysis provided in this study has shown the possibilities of the two methodological approaches as useful tools in dynamic portfolio management. The ML methods such as RF provide robust forecasts of future price movements, which were used in the second part of the analysis, where the GST approach was used to rank the stock market indices based on the RF forecasts. This was a basic exercise, in which we have taken into consideration that investors observe several performance measures at once.

4 Conclusion

Note: Max, Min, Std. Dev., Skew, Kurt, and *N* denote maximal value, minimal value, standard deviation, coefficients of skewness and kurtosis, and a number of observations, respectively.

Note: Total – total return, SD – standard deviation, Lower SD – lower standard deviation, CE – Certain Equivalent, 1 5 and 15 refer to values of γ. R/Risk – mean return over one unit of risk (measured via standard deviation), Divers – diversification degree (DI index). Bolded values indicate the best-performing portfolio in each row.

This work filled one of the gaps in the portfolio selection literature by combining RF with GST and it is the main contribution of the chapter.

The RF algorithm is used for forecasting values for each of the observed stock indices based on previous values (closing, high, low) and the selected technical indicators calculated from them. Based on the predictions, the GRA approach is then used to rank the stocks for the dynamic portfolio selection.

The results on forecasting index values using RF corroborate other similar research that indicates the good performance of RF on such problems. This research showed that even simply using the fixed RF setup behaved reasonably well. Thus, it can be expected that tuning the RF algorithm find the optimal setup, i.e. optimizing its parameters should bring further improvement to its forecasting ability. We leave this for future work together with exploring other possibilities for improving the forecasting process.

The GRA approach and simulating investing strategies based on such approach which lay upon forecasted values made by the RF algorithm showed promising results. This should encourage further research on using GRA methodologies. An additional contribution of this research is that the criteria used for the ranking system are based on the investor's utility theory and not random variables. In this regard, it could be interesting to try to incorporate other criteria into the ranking system and possibly construct an automated procedure of adjusting weights used in the GRA approach following a certain strategy. Another future research idea is to analyze and compare more investment strategies and different forecasting and investment horizons.

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9 The role of blockchain in financial applications

Architecture, benefit, and challenges

Ahmed A. Elngar, Mohammed Kayed and Hosny H. Abo Emira

1 Introduction

The blockchain principle was started initially for bitcoin, which presents a publicly distributed and secured database. In Internet of things (IoT), there is a network of various devices which interact with each other without human intervention. It helps the quick transfer of data in an effective manner. The IoT-enabled devices lead to operational improvements in terms of efficiency, performance, and safety. The IoT can also be thought of as a one-unit global network. The implementation of IoT applications also projects revenue and growth in the IoT market. The IoT consists of intelligent devices or machines which communicate to other devices, things, machines objects, or infrastructure. Things in IoT referred to objects of the physical as well as a virtual world that has the capacity to integrate within the communication network. It can be static or dynamic.

The most simple and primary use for blockchain technology is its use as a payments system. Bitcoin and other cryptocurrencies operate both as digital money and also as a method to transfer payments in that money from around the World. These transactions require only an internet connection and are done instantly. While it is reliable that it may take many minutes for a transaction to be approved, the transaction itself is done in a matter of moments. These transactions are borderless, safe, and largely anonymous. Moreover, transaction costs are minimum, costing only a few cents per transaction making it a greatly cheaper way to send money around the world. A sender not wanting to pay the initial and continuous fees to accept credit cards could take electronic payment through a cryptocurrency instead for a part of the cost.

Nowadays cryptocurrency has become most popular in both industry and academia. As one of the most successful cryptocurrencies, Bitcoin has owned huge success with a specially designed data storage structure, transactions in the Bitcoin network could happen without any third party and the hub technology to build Bitcoin is blockchain. Blockchain could be considered a public ledger and all active transactions are stored in a list of blocks. This chain grows as new blocks are attached to it continuously. Asymmetric

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cryptography and distributed consensus algorithms have been executed for user security and ledger agreement. Blockchain technology generally has key characteristics of decentralization, persistency, and anonymity. With these traits, the blockchain can provide alternative solutions to satisfy these roles through the provision of a verifiable public record of all transactions which is distributed and can be decentralized in its administration.

Since it allows payment to be completed without any bank or any intermediary, blockchain can be used in several financial services such as digital assets, transmittal, and online payment. Additionally, it can also be employed in other fields including smart contracts, public services, IoT, reputation systems, and security services. Those fields prefer blockchain in multiple ways. First, blockchain is immutable. The transaction cannot tamper once it is inserted into the blockchain. Businesses that require high confidence and honesty can use blockchain to attract clients. Additionally, blockchain is distributed and can avoid the single point of the failure condition. As for smart contracts, the contract could be performed by miners automatically once the contract has been deployed on the blockchain.

In thinking about the opportunities of blockchain within the banking sector, there are a series of different potential avenues to explore that move beyond the typical discussion on transmittal services. Banking systems are large and involved, including a series of features such as back-end ledger keeping systems, record customer account details, transaction processing systems, such as cash machine networks, all the way through to trading and sales, over the trades, and money transfer systems.

2 Technical aspects of blockchain technology

2.1 Technology behind blockchain

Governments and corporates everywhere world are slowly and steadily realizing the worth of blockchain, which could be a new child on the block. It originated from the monetary circles and is pervasive in the business world. Its ardent supporters sincerely applaud it for its unbreakable and impenetrable security features. The shortest definition for blockchain is it's a distributed ledger. That is, it stores any list of transactions in a very peer-to-peer (P2P) network. Information in a blockchain is kept in mounted structures known as "blocks."

- **Cryptocurrency:** could be a digital currency within which encoding techniques are wont to regulate the generation of units of currency, and to verify the transfer of funds operative severally of a central bank.
- **Distributed ledger:** is information that's consensually shared and synchronal across the network unfolds across multiple sites, institutions, or geographies. It permits transactions to own public "witnesses," thereby creating a cyberattack additional difficult.

- **Smart contracts:** are agreements that are encoded in an exceedingly trojan horse and mechanically dead upon sure criteria being met. Benefits of smart contracts embody improved quality, reduced contract execution costs, and inflated speed. Sensible contracts are held on the blockchain.
- **Miners:** are the folks keeping the blockchain running by providing an enormous quantity of computing resources to competitors to resolve a cryptanalytic puzzle and upon finding the puzzle, they generate a block, and that they conjointly get rewarded. Miners contend to come up with a legitimate block of transactions. Miners collect all unfinished transactions from the decentralized network then they guess a random variety (nonce) to solve a cryptographic puzzle, on with success solving the puzzle they generate a block then they push that block into the network for verification from other nodes so different nodes when verification can add that block in their copy of the blockchain.
- **Nonce:** The cryptanalytic puzzle that miners solve is to spot the worth of the nowadays. A nonce could be a random variety that will be used just one time. Largely it's a random number with a mixture of some data. Blockchain adds a worth known as the nonce in every block. This nonce is sort of a salt side to the contents of a block. By adding nonce, the hash output of the contents of the block will change.
- **Hash**: Hashing is a cryptanalytic technique that maps input files to data of a hard and fast size output. Bitcoin uses the SHA-256 algorithmic program for it.

2.2 Working of blockchain

The blockchain is several blocks, which are completely open and the public to everyone. The public ledger in the blockchain is distributed in nature. The primary feature of blockchain is that once the data are recorded inside the ledger, then that data cannot be deleted. The blockchain work mechanism is every block already in the chain consists of the data, the hash to this data, and the previous hash. The data recorded in the blockchain depends on the kind of blockchain. If the blockchain is relevant to bitcoins, it will collect data for transactions, the data about the sender and receiver, and the number of bitcoins present in the network. Each block in the chain is should have a hash value that can be matched with the fingerprints. As the new block is generated, the hash of that block command also is generated. The hash of the block will be replaced with the modifications made in the block. Since the hash value is a very significant factor while making modifications in the block. If the hash value of any block will be exchanged, then it will not be in the identical block. Additional to the hash of the current block, the block also contains the hash of the previous block. This helps to make a chain by connecting the current block to the previous block. These features of a block in the chain performs blockchain more secure.

Suppose an example of a chain holding three blocks. As shown in Figure 9.1, each block consists of the hash value of the current block and the previous block. Block number 2 is p connected to block number 1, block number 3 is connected to block number 2 using the previous hash. The previous hash of the first block is 0000 because it is a first block that is not pointing backward to any block. This block is identified as the Genesis block. Guess somebody wants to tamper block number 2. With the tampering of the block, the hash value of that block will additionally be changed. In that case, the third block and the next blocks connected in the chain will be invalid because there is no valid hash present at that time. Replacing one block in the chain will appear in invalidating all the following blocks in the chain. To make it valid, this needs to change the hash value of all the next blocks. Though it is a great idea to make the blockchain secure it is not enough to stop tampering. With the improvement in computer technologies, thousands of hash values can be computed per second. Anyone can modify the hash of the current block and the following hash by employing computational technologies. In that case, these blocks will be valid even after tempering. Wherefore, to make it less dangerous, the blockchain offers a concept known as proof of work.

Applying the technique of proof of work, the work of the new block gets slowdown up to some limit. In this case of bitcoin, the calculation of proof of work needs time to add the new block in the chain. This technique improved the security of the blockchain. Because if someone will attempt to tamper with any block in the chain then he needs to recalculate the proof of work for all the next blocks which are very hard. Therefore, the combined use of hashing technique and the proof-of-work mechanism make the blockchain more confident.

One of the main advantages of blockchain is its distributed environment, which presents blockchain defend itself. Rather than the centralized system of controlling the chain, blockchain uses a peer-to-peer network. As the blockchain is open and public, anyone can register the network. After joining the network, the member will be getting a full copy of the chain. The node can authenticate using that copy whether everything is occurring in

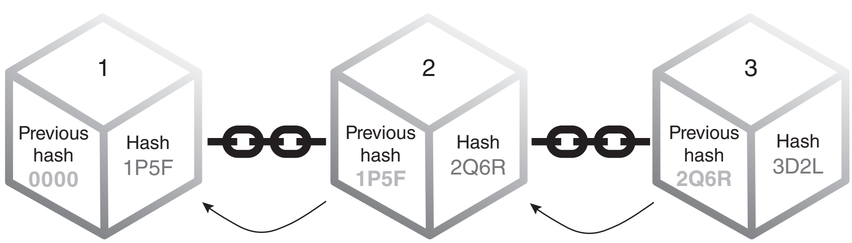

Figure 9.1 Blockchain structure.

order or not. Now if somebody produces a new block, the block will be sent to everyone already in the network. Every node will confirm that block to ensure that the block is genuine or tempered. After confirmation, the new block that is produced recently and verified will be added by each node in their copy of the chain. When an agreement is created by all the nodes in the network. They make a consensus on which block is authentic and which is not. If the block is valid, it will be attached to the chain. If the block is tampered with, then it will be denied by all the nodes. Therefore, to temper with one block, one must temper with all the blocks already in the chain and recalculate the proof of work for all blocks. After doing that, only the tempered block will be accepted by others blocks present in the network, which is nearly impossible to achieve. That is why the combination of hash and proof of work is a secure mechanism for blockchain.

The blockchains are developing day by day. Smart contracts are the most recent evolution of the blockchain. The smart contacts are used to transfer coins between the nodes in the network automatically based on some conditions and are listed in the blockchain. Blockchain technology is important for many users these days. Additionally, the transfer of bitcoin, this technology can also be used in different sectors as well, like managing medical records, tax collection, smart homes, etc.

2.3 Blockchain architecture

The block design structure is composed mainly of the block header and the block body which contains a list of transactions as shown in Figure 9.2. In particular, the block header contains various fields, one of which is a version number to track software of protocol upgrades. Also, the header contains a timestamp, block size, and the number of transactions. Merkle root hash is the hash value of all the transactions in the current block, Parent block hash is a 256-bit hash value that points to the previous block. Merkle root hash is the hash value of all the transactions in the current block. Merkle tree hashing is commonly used in distributed systems and P2P networks for efficient data verification. The nonce field is used for the proof-of-work algorithm, and it is the trial counter value that produced the hash with leading zeros. The difficulty target specifies the number of leading zeros and is used to keep the block time. The difficulty target is adjustable periodically and is increased as the computation power of hardware increases over time. The block time is set by design to account for the propagation time of blocks to reach all miners, and for all miners to reach a consensus.

The block body is composed of a transaction counter and transactions. The maximum number of transactions that a block can contain depends on the block size and the size of each transaction. Blockchain uses an asymmetric cryptography mechanism to validate the authentication of transactions. A digital signature based on asymmetric cryptography is used in an untrustworthy environment.

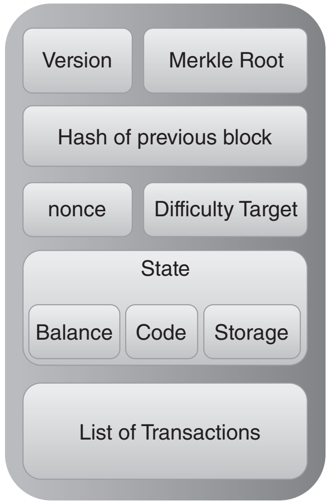

Figure 9.2 Block structure.

2.4 Types of blockchain

Blockchain is categorized into three major types based on the users' availability and accessibility.

1. **Public (permissionless) blockchain**
   A public blockchain is a decentralized, open ledger in which any node can enter the network and can engage in the processing, storage, and validation of the transaction data through a consensus mechanism.
2. **Private (permissioned) blockchain**
   The private blockchain is a limited one, where no one can quickly become a part of the network. It is a type of centralized blockchain controlled by a central authority for accessibility. The data read authorization in the private blockchain is opened to the public selectively. Private blockchain is specific to limited organizations or small industries. Vote counting, digital identity, asset ownership, and supply chain management are different kinds of use cases of the private blockchain.
3. **Consortium blockchain**
   The consortium blockchain is a partially decentralized chain. The pre-selected node will have the authority to choose the type of service in advance. Remaining nodes may have access to the blockchain transactions, but not in the consensus process. Hyperledger and R3CEV are examples of consortium blockchain as shown in Figure 9.3. Namely Bitcoin, Ethereum, and Hyperledger fabric.

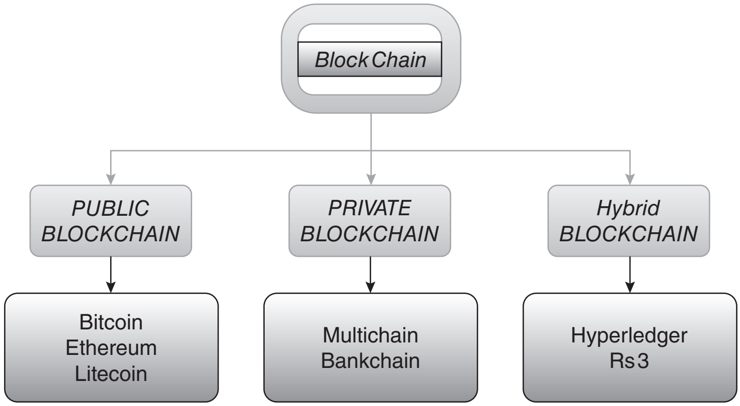

Figure 9.3 Types of blockchain.

2.5 Key characteristics of blockchain

Decentralization: In traditional centralized transaction systems, each transaction needs to be confirmed through the central trusted agency necessarily rising the cost and the performance bottlenecks at the central servers. Otherwise, a transaction in the blockchain network can be transferred between any two peers (P2P) without authentication by the central agency. In this way, blockchain can significantly decrease the server costs including the development cost and the operation cost and decrease the performance bottlenecks at the central server.

Persistency: Considering each of the transactions spreading across the network needs to be approved and recorded in blocks distributed in all networks, it is nearly difficult to tamper. Additionally, each broadcasted block would be confirmed by other nodes and transactions would be checked. Therefore, any falsification could be recognized easily.

Anonymity: All users can communicate with the blockchain network with a generated address. Moreover, a user could generate many addresses to avoid identity exposure. There is no longer any central combination keeping users' private information. This mechanism preserves a certain measure of privacy on the transactions included in the blockchain. Note that blockchain cannot guarantee complete privacy preservation due to the fundamental constraint.

Auditability: Since all of the transactions on the blockchain are approved and recorded with a timestamp, users can easily verify and track the previous records by accessing any node in the distributed network. In the Bitcoin blockchain, each transaction could be tracked to previous transactions iteratively. It enhances the traceability and transparency of the data stored in the blockchain.

3 Banking benefits from blockchain technology

There are a few benefits for the financial services industry to be achieved by using distributed ledger technologies can name as blockchain. Traditionally, the financial services industry is known for its legacy systems and some banks have stacks of legacy systems, therefore, not surprising that the financial services industry has embraced blockchain to improve many of their old systems and, along the way, save a lot of money (which, not surprisingly, might be the main reason for them to move to the blockchain). Using a distributed ledger, banks can trade faster and cheaper and become more efficient. Some of the benefits are:

3.1 Faster payments

By establishing a decentralized channel for payments, banking companies can use developing technologies to facilitate faster payments and reduce the fees of processing them. By offering larger security and lower cost of sending payments, banks could propose a new level of service, produce new products to the market, and finally be able to race with innovative fintech startups. Moreover, by adopting blockchain, banks will be able to decrease the need for verification from third parties and accelerate the processing times for traditional bank transfers. Previously in 2016, 90% of the European Payments Council members believed that blockchain would change the industry essentially by 2025.

3.2 Clearance and settlement systems

A distributed ledger technology (DLT) like blockchain could approve bank transactions to be resolved directly and keep track of them better than existing protocols such as Society for Worldwide Interbank Financial Communications (SWIFT). A common bank transfer takes a few days to achieve because it is limited by the way our financial infrastructure was built.

Moving money around the world is a logistical challenge for several banks. A simple bank transfer needs to avoid a complex system of intermediaries such as custodial services before it reaches its destination. Furthermore, the bank balances require to be reconciled over the global financial system, which contains a broad network of funds, asset administrators, dealers, and more. For example, if you would like to send money from an account in a Chinese bank to one in the United States, that transfer will be executed through the SWIFT.

The centralized SWIFT protocol processes just the payment orders. The actual money is prepared through a system of intermediaries. Each of them arrives at an additional cost and takes a lot of time. A decentralized ledger of transactions like blockchain could allow banks to keep track of all the transactions publicly and transparently. Banks will not need to rely on a network of custodial services and administrative organizations like SWIFT. They could simply verify transactions directly on a public blockchain.

3.3 Buying and selling assets

By removing the agent and asset rights transfer, blockchain decreases the asset exchange fees and reduces the instability of the traditional protection market. Moving securities on a blockchain could save each year in global trade processing costs.

Buying and selling assets like stocks, products, or debts are based on keeping track of who owns what. Financial businesses fulfill this through a complex network of exchanges, agents, clearinghouses, central security safes, and maintenance banks. All these different individuals have been constructed around an outdated system of paper claims. The system is not only slow but riddled with flaws and prone to deception. Performing such transactions electronically is complex because most of the time, buyers and sellers do not rely on the same maintenance banks, and these don't regularly rely on trusted third parties to hold above all the paper certificates.

If you are buying or selling an asset, the order will be carried through numerous third parties. That is why transferring ownership is so complex. Each party keeps its own version of the accuracy in a separate ledger. The system is not only inefficient but also imprecise.

Blockchain will revolutionize financial businesses by creating a decentralized database of digital assets. A distributed ledger allows transferring the rights of an asset through cryptographic tokens that can render such assets off-chain. Cryptocurrencies like Bitcoin and Ethereum fulfill that with purely digital assets, but many blockchain businesses are now working on solutions that would help us tokenize real-world assets such as gold or real estate. Cutting out the agent will also lower the asset transfer fees and accelerate the process significantly.

3.4 Fundraising

Raising money through venture capital is a complex process today. Most of the time, it appears like Entrepreneurs put decks together, carry out countless meetings with partners, develop long discussions overvaluation and investment, and eventually, hope to exchange their company for payment. Blockchain companies are accelerating the process by raising funds with several options. These include Initial exchange offerings, equity token offerings, and security token offerings (STOs). STO is currently the common popular option because it is legally protected. To profit from this model, projects need to pass a due diligence process. Previously, initial coin offerings (ICOs) were more popular but are now considered spammy and unreliable.

3.5 Credit and loans

Traditional banking companies finance loans by using a system of credit reporting. With blockchain, we are looking at the future of peer-to-peer accommodations, faster and more secure investment processes in general, and even complex scheduled investments that can approximate syndicated investment structures or mortgages. Banks that process investment applications evaluate the risk by studying factors such as credit score, homeownership status, or debt to income ratio. To get all that information, they need to ask for your credit report produced by specialized credit companies. Such centralized policies are often detrimental to consumers because they contain erroneous information. Besides, concentrating such sensitive information within a small number of companies makes it very unsafe. For example, one of them got hacked and exposed the credit information of over 145 million Americans. Now you can see why blockchain offers a more secure, efficient, and more competitive way of processing loan applications.

3.6 Trade finance

Blockchain is set to revolutionize the trade finance sector. Trade finance applies to all the financial enterprises related to international trade and commerce. Many trade finance activities today still rely on paperwork such as invoices, letters of credit, or bills. Multiple order management systems provide carrying out this work online, but the process takes a lot of time.

Blockchain-based trade finance will streamline the exchange process by getting rid of such time-consuming manual processes, and paperwork. For example, in common trade finance systems, all the partners need to maintain their own database for transaction-related records. And all these databases need to be continuously adjusted against each other. A single mistake in one record may be duplicated to the copies of this document in other databases.

With blockchain, there is no need to keep any copies of the same document. That is because the information can be combined into one digital record, which is updated in real-time and can be reached by all network members.

3.7 Digital identity verification

Banks would not be able to perform on-line monetary transactions while not biometric identification. However, the verification method consists of many completely different steps that buyers do not like. It is often face-to-face checking, a variety of authentication (for example, whenever you log into the service), or authorization. For security reasons, these steps ought to be taken for each new service provider. With blockchain, consumers and firms can get pleasure from accelerated verification processes. That is because blockchain will build it attainable to use identity verification for alternative services securely. The foremost standard innovation during this space is zero-knowledge proof (ZKP). Several countries and enormous companies are currently performing on solutions supported by ZKP.

Using blockchains, users are able to opt for Whatever needed to spot themselves and with whom they conform to share their identity. They will ought to register their identity on the blockchain solely once. There is no need for continuance of that registration for each service supplier if those suppliers also are battery powered by the blockchain. Naturally, storing this sort of data on a blockchain also ensures its security.

3.8 Accounting and auditing

Accounting has been a nearly slow area to digitize. One of the reasons behind that is the need to match the strict supervisory requirements about data integrity and validity. That is why accounting is probably a different area that could be transformed with blockchain. Specialists think that the technology will simplify compliance and streamline the regular double-entry ledger keeping systems. Instead of keeping separate records based on transaction receiving, companies can add transactions directly into a common register. All the records in the register will be distributed. The records will be more honest and secure. A blockchain would act like a digital notary that verifies all the transactions. Blockchain smart contracts could be used in such applications to pay for bills automatically.

3.9 P2P transfers

P2P transfers enable customers to transfer funds from their bank accounts or credit cards to other accounts online. Currently, there are several P2P transfer applications available in the business. But they all issue with certain limitations. For example, some of them enable you to transfer money only within a specific geographical region. Others do not allow you to transfer money if both individuals are in the same country. Besides, P2P services may require large fees for their services and not be secure enough for collecting sensitive customer data. All these problems can be approached with blockchain. The technology will serve to decentralize applications for peer-to-peer transfers. Blockchain has no geographical limitations, allowing P2P transfer over the entire globe. Besides, blockchain-based transactions will be done in real time, so the receivers won't have to wait many days until they receive money.

4 Blockchain in banking

4.1 Blockchain technology developments for bank ledgers and financial accounting

The potential of blockchain technology to partially replace trusted third parties, regularly employed in multiple roles in finance as managers, payment providers, poolers of risk, and in insurance situations. Identify that the main roles of such trusted third parties are to provide functionality such as validation of trade transactions, prevention of duplicated transactions, the double-spending issue, recording of transactions in the event of disputes over contract settlements or deliverables, and acting as agents on behalf of associates or members. The blockchain can provide alternative solutions to fulfill those roles through the provision of a verifiable public record of all transactions which is distributed and can be decentralized in its administration.

In thinking about the possibilities of blockchain functionality within the banking sector, there is a range of several potential avenues to investigate that move beyond the typical discussion on remittance services. Banking systems are deep and complex, including a range of features such as back-end bookkeeping systems, which record customer account details, transaction processing systems, such as cash machine networks, all the way through to trading and sales, over the counter trades, and interbank money transfer systems. Today, we are however unaware of any papers that go beyond this high-level discussion and detail exactly how and what form blockchain technology may provide benefit in these aspects in banking settings.

One of the potential incentives for financial institutions, banks, insurers, and banking regulators for the development of distributed blockchain technologies for these types of applications involves the reduction of overhead and costs associated with audit and regulation. In addition, more automation and efficiency in transaction processing, clearing, and reconciliation can help to reduce counterparty credit risks. Some core features that blockchain approaches share can be both beneficial and detrimental.

- Immutability of itemized elements in the blockchain. A blockchain is effectively a distributed transaction database or ledger that is immutable, in that data stored in the blockchain cannot be modified. However, some versions of blockchain frameworks are starting to develop that alter the perception of immutability. This proposes the irreversibility of the regular blockchain framework by only allowing entrance to data for secure computations in reversible and controllable manners. They also ensure that only the original data owner(s) ever sees the raw data.
- Transparency of information presented on the blockchain. Many blockchains being created are publicly accessible by anyone with an internet connection and are replicated countless times on cooperating nodes in the network, though private versions or controlled blockchain networks are emerging. The extent of the application needs private versus public components. In current regulatory changes in banking and financial institutions, there are numerous competing constraints that emphasize both the importance of financial disclosure, requiring financial institutions to demonstrate transparency in their reporting and their relationship with regulators, and on the other side, there are also fiduciary

duties that institutions maintain in upholding data privacy on behalf of their clients. Therefore, alternative approaches to private versus public blockchain networks are also being explored where instead the data on a public ledger may have different levels of data integrity structure protocols that implement possibilities such as encryption of data stored in blockchains.

5 Blockchain technology and its potential for financial applications

Blockchain technology over the past years has become one of the focal points of several financial practitioners eager to understand how it could possibly alter their ways of doing business. We outline where think blockchain technology is likely to matter most when it comes to financial applications.

5.1 Payment systems

It seems fair to say that it all began there for finding a cheap and secure way to make decentralized payments. The first implementation of the Bitcoin protocol generated growing interest because bitcoin payments worked and despite the setbacks and negative publicity. It has been recognized as an effective means of getting international transfers and paying remittances, with lower transaction costs than standard banking fees and a much faster settlement of about 10 minutes for the first confirmation as opposed to a couple of days for an international bank transfer. And blockchain technology has been the subject of increasing interest and various experiments as a payment solution. Visa has tested the blockchain while a DLT-based solution has been developed by the Korean KB Kookmin Bank for its fund transfers, currently done on SWIFT.

One of the key subjects is whether the Bitcoin network or any other DLT-like network using an agreement mechanism will be able to perform transaction throughput like major payment networks such as Visa or Mastercard. And this scalability issue has sometimes set off discussions on the technological adjustments that would be required such as whether the block size should be increased or not. There has also been a lot of discussion as to what types of payments should be transferred on blockchains. For example, several think that the Bitcoin blockchain should not be used for trivial payments but that its bandwidth should be saved for authenticating and storing key consolidated information such as regular net balances of sidechains dedicated to several types of micropayments.

It is still too early to know where those technologies will end up falling, but it is important to bear in mind that what is particularly interesting with DLT is its transactional generality, not only can it be used for payments, but it can be used for many other applications such as storing digital assets or digital certificates and proof of existence information.

5.2 Corporate finance and governance

Blockchain is full of promises when it becomes to corporate finance. This is principally due to the fact that it could be used as a firm's new informational backbone. Blockchain technology resonates expressly well with chief financial administrators and treasurers, because of the ownership traceability it could provide. Certainly, a firm's ownership is not always easy to trace. Surely, publicly traded businesses have to know their important shareholders, and regulations force shareholders to publish ownership when crossing certain thresholds. However, minority shareholders are usually difficult to trace, so that in certain situations such as a corporate takeover, a firm's administration may have a difficult time reaching out to them. DLT could produce significant improvements to these situations where management is unsure of this information. And DLT could also turn out to be really useful for corporate governance, expediting shareholder consultation at annual general conferences through secure electronic voting. This more granular tracking of a firm's stakeholders should also very facilitate dividend payouts to shareholders or card payments to bondholders.

5.3 Financial accounting, trade finance, and supply chain management

Their beliefs in blockchain are essentially based on high expectations that an almost exhaustive recording of all financial transactions including a corporation could do wonders for its management, not just its main financial officer or accountant, but also its chief accountant, legal advice, or purchasing manager. Just as any observers expect that corporate governance should become more inclusive, financial accounting and management could become more careful with almost real-time updates of a firm's stability sheet, income, or cash progress statements. Similarly, enterprise finance, which to this day still involves letters of credit and fax-based paperwork, could benefit from blockchain technology. And previously many DLT-based initiatives for promoting P2P commerce, and its financing, have emerged such as working on fostering a smart contract solution to supervise all phases of a typical trade agreement from order, shipment, and invoice to final payment. Blockchain technology is expected to force a firm's administrators to reassess their various organizational and management processes.

5.4 Financial reporting and compliance

Blockchain appears also very hopeful for automating financial reporting and enforcing compliance methods. Certainly, as a complete and immutable repository of a firm's past transactions, it should support an auditor's work and even a regulator's monitoring of a firm's activities. For banks and financial systems in general, this feature seems particularly relevant. Indeed, the

2008 global financial crisis has triggered new and more stringent prudential regulations for banks or for insurers. One could hope that implementing the capital or liquidity requirements embedded in these directives should be helped by a shared blockchain infrastructure. This vision of leveraging DLT for automating compliance systems still seems futuristic but since the technology is getting a lot of recognition from regulators and audit firms alike, DLT is fueling innovative thoughts on how to enhance and simplify compliance systems by redesigning reporting channels and automating financial reports.

5.5 Crowdfunding and P2P lending

Blockchain's ability to track ownership in a distributed and immutable way has been appealing to both issuers and investors, hence it should not be unexpected that some crowdfunding platforms have started to examine using blockchain technology to provide their investors with investment e-certificates. But just as we discussed before that DLT may turn out a potent means of disintermediating centralized platforms, its attractiveness for crowdfunding and P2P lending goes beyond its traceability improvements.

Table 9.1 Blockchain benefits analysis framework for financial services

Paper	*Factors*	*Description*
Wang et al. (2019) Clohessy and Acton (2019)	Privacy	Blockchain transactions can offer users better privacy, permitting users to own their data and not allowing third-party agents to misuse and obtain data
Queiroz and Wamba (2019)	Transparency	Transparency is improved because the transactions are shared through the network
Mendling et al. (2018)	Enhanced security	Blockchain offers financial institutions with better security compared to storing all data in a central database and avoids destruction from attacks on the database
Lakhani and Iansiti (2017)	Efficiency	Blockchain presents banks with a quick decrease in overhead costs
Wang et al. (2019)	Immutability	Transaction records in the blockchain cannot be modified since the blockchain ledger can keep on permanent and unaltered
Clohessy and Acton (2019)	Faster transactions	Blockchain will allow payments to reach beneficiaries faster with fewer steps

And some startups have offered their users to run crowdfunding campaigns with fiat currencies, Bitcoin, or the startup's native tokens, thus leaving clients free to choose their way of investing (Table 9.1).

6 Challenges

Achieving consensus: There is a need for agreement among a blockchain network's members. Because the ledger is distributed between all participants in the blockchain, any protocol modifications must be approved by all members. A potential solution, potential in a permission network, would be to allow one or a few participants the authority to make protocol modifications that were required upon the entire network. But requires important trust in the authorized participants.

Standardization: There is additionally a requirement for standardization of blockchain network designs, which can cause important problems in their implementation and recognition by businesses. Many local and international businesses are trying to establish commonly accepted technical rules.

Interoperability: Current businesses will engage challenges related to the interoperability of blockchain platforms with their existing internal systems. It remains to be seen how blockchains of multiple businesses might engage with each other.

Scalability: The need to improve the scale of distributed ledger systems also represents a challenge, individually for permissionless blockchains that use a race to resolve a computer problem to verify a transaction. The race uses a large amount of computing power, limiting the time with which new transactions can be confirmed. All networks permission or permissionless will need a large volume of storage resources, as each node in the network will manage its copy of the distributed ledger.

Efficiency: There will be tradeoffs between the blockchain ability to avoid relying on trusted parties and its efficiency. A complicated computational system to verify transactions is less efficient than a system more reliant on the responsibility of permission nodes in the network but offers the advantage of not requiring everyone in the network to conform to trust certain parties.

Immutability: Once added to the blockchain, a transaction is unchanging. Trades that regulator demand to be changed can only be changed by tendering an equal and offsetting trade, which the parties involved in the primary trade will both need to accept.

Legal uncertainty: Firms do not have evidence of the laws and regulations that will apply to DLT implementations in cases of cheating, bankruptcy, and other failure scenarios. This is particularly a problem for firms that operate in multiple domains.

Security: While the decreased reliance on a central authority and the truth that copies of the ledger are stored in more than one place enhance the single point of failure problem present in many legacy systems, blockchain's distributed nature additionally creates security concerns. The more partners in the network make more points of attack there are for cybercriminals to target. If cybercriminals can steal information of a user required to submit a trade, they could create fraudulent, and changeless transactions.

Liquidity: The use of a blockchain for ownership transfers could drastically decrease the uncertainty associated with current settlement conventions, but it will improve the importance of liquidity. Funds and assets must be in proper form and location for such expedited settlement.

Privacy: Blockchain's potential impact on the confidentiality and rate of information transfer about record modifications may also be of concern to some users. For example, in finance the recovery and analysis of data are key to a firm's competitive advantage. Some firms may be resistant to participate in a shared database in case of information leakage that could cost the firm's business.

7 Related work

Different countries and firms are using different approaches to the blockchain. Econometric models have been adapted and applied to improve analysis and make businesses more competitive (Ji et al., 2020).

Blockchain as a technology has the potential to be exceptionally useful to the investment and banking industry as an eco-system (Beck et al., 2017; Hassani et al., 2018).

Literature on the benefits of implementing blockchain in the banking sector is available from various sources, such as industry-published whitepapers, blogs, wikis, and conference proceedings (Hyvärinen et al., 2017; Larios-Hernández, 2017; Cole et al., 2019).

Banks primarily apply blockchain technology for fund transfers, registrations, and maintaining back-end utilities (Zheng et al., 2018; Andoni et al., 2019; Taylor, 2019).

This technology works like a distributed ledger and is completely open to anyone and everyone in the network. Once the data is registered in the blockchain, it is very difficult to alter or transform it, making the blockchain inherently secure (Lakhani and Iansiti, 2017; Pratap et al., 2018).

Jaag and Bach (2017) studied the opportunities that may arise from blockchain technology in postal organizations, such as decentralized platforms, secured record-keeping, and fast transaction systems.

This technology is an accurate representation of data structure that keeps track of multiple transactions and safeguards the transparency, security, and decentralization of the data (Andoni et al., 2019).

Blockchain technology is expected to bring greater transparency to monetary transactions and advance the efficacy of countries' financial systems.

Blockchain technology can provide a new revolution, especially in the banking sector with better payment clearing mechanisms and upgraded credit information and management systems, which would lead to a more efficient banking system.

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10 Using Computer Blockchain Technology to Analyze the Development Trend of China's Modern Financial Industry

Zhenxing Bian

1 Introduction

Due to the continuous and rapid development of the world economy and the adjustment of the industrial system of various countries in the world, the proportion of the financial industry has gradually increased, and the financial industry occupies an important position in the entire national economy [1]. After China joined the World Trade Organization, with the continuous improvement of the multi-stage and multi-functional financial market system, the banking transaction and information system service industry has gradually improved. Therefore, China has basically established securities and futures markets, inter-bank foreign exchange markets, and foreign exchange markets. Basically realized the various developments of commercial banks, securities companies, insurance companies, trust companies, social security funds, and other legal persons [2]. Since 2008, China's rapid economic growth has been disrupted by various pressures such as inflation. To this end, the Chinese government amended the "Banking Law", re-implemented, formulated, and implemented the monetary policy of the People's Bank of China, and expanded the responsibility for maintaining the monetary policy. The People's Bank of China attaches great importance to the implementation effects of our country's monetary policy and must maximize its effectiveness, scientificity, pertinence, and forward-looking nature and adjust our country's monetary policy. According to the changes in the overall financial situation at home and abroad, use macro-control to adjust the development direction of our country's financial industry [3].

Computer blockchain technology originated in Bitcoin, and computer blockchain technology is a way of verification, transmission, storage, and delivery that is not attached to a third-party platform [4]. This technology has high security and can improve the transparency of financial industry transactions, but its essence is database technology, mainly to solve some special problems. Prior to this, some financial institutions have used the database for data storage, but for the sake of security and confidentiality, the technology has not been disclosed, and the application of the technology also requires a lot of financial resources [5]. With the rapid development of

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the times, the computer blockchain technology will completely break the original technology, and its main characteristics include: first, centralization [6]. Each node of the blockchain can operate by itself to realize the transmission, management, and verification of information. Second, openness. It is more transparent, and all data information is shared. Third, independence. This technology will not rely on third-party platforms and is relatively independent [7]. Fourth, safety. Only by mastering more than 50% of the nodes can control the system be achieved, so it has super-high security. Fifth, anonymity. In actual work, the information passing the node does not require identity verification, unless there are special circumstances, such as legal requirements [8].

With now the age of the Internet, a large number of transactions in China's modern financial industry have moved from offline to online. How to ensure the safety and efficiency of online transactions has become one of the problems waiting to be resolved in the financial industry [9]. The speed, efficiency, and scalability of the Internet have greatly increased the volume of transactions and transaction information and increased the difficulty of transaction management in the financial industry. In recent years, a series of financial information security incidents have continued to emerge worldwide. Under the lure of huge profits, criminals have stolen a large amount of user information through computer viruses and hacker attacks, causing huge losses to the financial industry [10].

2 Method

2.1 Financial Cobb–Douglas Algorithm

Products developed through big data innovation have unique ideas. At present, there are no similar related products and competitive rivals in the national market. If the product life cycle is not considered, the supply and demand relationship in the product market will be affected by the cost of data resources. And the impact of innovation investment. Based on the Cobb–Douglas production function theory, the production function of big data innovation can be derived as follows:

$$R(x,y)=bx_{\alpha}y_{\beta} \tag{1}$$

The producer's cost function is as follows:

$$C(x,y)=x+y \tag{2}$$

As a rational producer, producers all follow the principle of maximizing corporate profits. Therefore, the producer's profit function is:

$$\pi(x,y)=R(x,y)-C(x,y)$$

$$\text{IN: } \pi(x,y) = bx^{\alpha}y^{\beta} - x - y \tag{3}$$

According to formula (3), find the partial derivatives of x and y respectively, and set $\frac{\partial \pi(x,y)}{\partial x} = 0$, we can get:

$$bax^{\alpha-1}y^{\beta} - 1 = 0 \tag{4}$$

Let $\frac{\partial \pi(x,y)}{\partial x} = 0$ we can get:

$$b\beta x^{\alpha}y^{\beta-1} - 1 \tag{5}$$

Solve the simultaneous equations (4) and (5):

$$x = \alpha\beta^{-1}y \tag{6}$$

Incorporating equation (6) into equations (4) and (5) respectively to solve:

$$x = \left(b^{-1}\alpha^{\beta-1}\beta^{-\beta}\right)^{\frac{1}{\alpha+\beta-1}}$$

$$y = (b^{-1}\beta^{\alpha-1}\alpha^{-\alpha})^{\frac{1}{\alpha+\beta-1}}$$

Analysis can get:

Reasoning theory 1: From equation (6), it can be seen that *b*, *α*, and *β* have a proportional linear relationship. In other words, there is a positive interaction between the resources of the financial industry and innovation investment. The richer the information on financial resources, the higher the intensity of innovation investment. On the contrary, the increase in innovation investment costs, the better the innovation results, and the resources for innovative products are gradually accumulating.

Reasoning theory 2: When there is a positive linear relationship between financial industry resources and innovation investment, production profits will reach the maximum. But the amount of benefit varies according to the prices of *b*, *α*, and *β*. Calculate the second derivative of *x* and *y* according to formula (3):

$$\frac{d\pi(x,y)}{dx^2} = b\alpha(\alpha-1)x^{\alpha-2}y^{\beta} < 0 \tag{7}$$

$$\frac{d\pi^2(x,y)}{dy^2} = b\beta(\beta-1)x^{\alpha}y^{\beta-2} < 0 \tag{8}$$

2.2 Promote the Informatization of the Financial Industry

With the development and wide application of computer technology and the rapid development of information technology with the Internet as the core, "Internet finance" came into being. The development trend of financial industry informatization is also becoming increasingly fierce. Against this historical background of huge economic development and the transformation of core technology platforms, our country's financial industry is facing new opportunities and challenges. In all aspects of financial activities and financial management, financial informationization means the deep development of modern network information technology. Actively use financial and economic information resources to accelerate the dynamic development of financial modernization. With the continuous development of information technology and economic globalization, financial services and financial innovation have become the core of the modern economy. Therefore, on the road to future development, we should actively develop Internet finance and continue to promote financial informatization.

2.3 Improve the Operating System of Financial Industry Institutions and Improve Their Competitiveness in Various Industries

Under our country's current financial industry development system, the system and organizational structure of financial institutions tend to be unified, and system innovation is difficult to achieve, especially the strategic planning of the banking industry is simpler. Therefore, our country must strengthen the supervision of the financial industry and implement policies and legal governance in accordance with the needs of market development. At the same time, establish a special regulatory agency to conduct comprehensive supervision and management of the financial industry, and realize the transition from single supervision to mixed supervision, and from institutional supervision to functional supervision. Establish an effective financial service firewall to ensure the security of funds and information, improve the risk early warning system, and gradually establish a sound supervision system

2.4 Propose a System Suitable for the Development of Our Country's Modern Financial Industry

Our country must propose a system suitable for the development of our country's modern financial industry, so that our country's currency market and capital market have perfect characteristics under the domestic market operation mechanism, and at the same time establish a system that is compatible with the development of our country's modern financial industry.

3 Experiment

3.1 Subject

Based on the financial Cobb–Douglas algorithm, this chapter analyzes the development trend of our country's modern financial industry through computer area chain technology. Taking each province of our country as the research object, by investigating the financial development level of each province, because the financial development level plays a very important role in the economic development of our country, this article uses comparative analysis, theoretical analysis, and quantitative analysis to study our country's modern what is the development trend of the financial industry?

3.2 Experimental Method

1 Literature research method

Literature research is the primary method of this article. Based on a comprehensive review of academic journal literature and related research reports of research institutions, this article has a basic understanding of the research hotspots and research gaps in the financial economy and then determines the research direction and basic ideas of this article on this basis, and strengthens The theoretical basis of this article extends the research scope and practice connotation.

2 Case study method

This article takes the provinces of our country as the research object and proposes development countermeasures with applicability and promotion significance through current situation assessment, feature analysis, and problem summary.

3 Comparative research method

Comparative research is a method of comparative research on a group of similar objects. This chapter mainly conducts a comparative study of two aspects: First, a comparative analysis of the weights of the four types of financial economy "basic-technical-integrated-service" to evaluate the contribution of the four types of the digital economy to the overall economic development Second, it is based on the relevant statistical data of each subdivision evaluation index to analyze the development trend of each specific index.

4 Qualitative research method

The organic combination of qualitative research and quantitative research is adopted. Focus on analyzing how to analyze and research the financial and economic development of each province.

4 Results

Through a series of analysis and research, we can know that with the reform and opening up and the changes in national policies, the economy of our country's financial industry has greatly improved compared with before. Due to financial bonds, financial assets and third-party payments, and other financial industry-related data. This article uses chart software to draw diagrams, as shown in Figure 10.1:

From Figure 10.1, we can see that our country's provinces are specifically viewed from the east and the middle. From 2011 to 2015, our country's financial development has shown an upward trend. The east has developed faster than the central and western regions due to financial resource endowments and geographic regions, but the western regions have developed faster due to national policies. The support of the country has developed rapidly. Since the beginning of reform and opening up, our country's policy has proposed that opening to the outside world should give priority to the eastern region. The Chinese government has proposed the strategy of "Eastern Coastal Regions Take the Lead in Development". The eastern region of our country has developed rapidly with the support of national policies and advantageous geographical location, which has driven China's financial sector. Compared with the rapid development of the financial economy in the eastern region of our country, the financial development in the western region is relatively slow, and the financial development of the two regions has widened the gap. Compared with policies such as the rise of the east, the large-scale development of the northwest, and the revitalization of the northeast, the central country's national policies are not perfect, the economic system reform is relatively backward, the level of marketization is low, the vitality of financial development is insufficient, and the flow of funds and labor and other factors between regions is unbalanced, etc. The

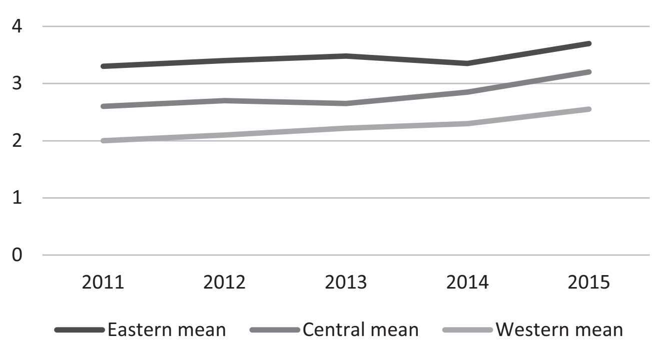

Figure 10.1 The level of financial development in our country's provinces from 2011 to 2015.

reasons have led to a decline in the financial development of central China as an inevitable trend.

By analyzing the movement trajectory of the financial center of gravity, this article can see the trend and direction of regional finance within a certain time range. As shown in Table 10.1:

It can be seen from Table 10.1 that during the period from 2011 to 2016, the center of our country's financial development level was mainly moved to the east and the moving distance did not change much. The moving distance from 2014 to 2015 was larger than before, respectively, 27 km and 78 km, but still biased toward the east. It can be seen from the changes in latitude and longitude that the range of trajectory fluctuations from 2011 to 2015 is relatively small, all moving within the eastern region of our country, and our country's financial center of gravity is still in the eastern region.

This article uses computer blockchain technology to analyze the development trend of our country's modern financial industry and applies computer blockchain technology to our country's financial industry. Our country's financial industry urgently needs a new technology or means to change this

Table 10.1 2011–2015 our country's financial development level center of gravity

Years	*Longitude*	*Latitude*	*Moving distance*
2011	113.577	33.38533	6.147988
2012	113.5309	33.34065	7.134375
2013	113.45	33.2816	11.13086
2014	113.2699	33.1136	27.36506
2015	113.3544	33.81828	78.85811

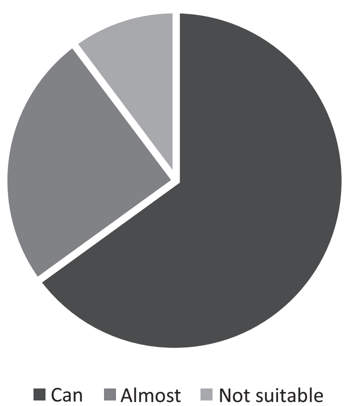

Figure 10.2 Views on computer blockchain technology.

status quo. Blockchain technology provides a good medicine for it. Through the views of people in our country's financial industry to understand how computer blockchain technology is as shown in Figure 10.2:

Computer blockchain technology can realize an efficient and low-cost transaction model: through a peer-to-peer transaction model, the blockchain can eliminate third-party intermediate links and achieve peer-to-peer connection, which greatly reduces the possibility of errors in the information transmission process. The computer program automatically confirms and executes the transaction results of both parties, greatly reducing the manual workload and improving the efficiency of financial transactions and settlements. The anonymity of blockchain technology ensures that customers can choose whether to disclose information according to their needs in secure transactions. The personal identification information of both parties to the transaction is effectively protected. If the computer blockchain technology can be fully applied to the financial industry, it will trigger the transformation of traditional financial transactions, simplify a large number of tedious work processes through technical means, and improve the security and efficiency of transactions.

5 Conclusion

In the above series of research and discussion, this article analyzes the development trend of our country's financial industry by using computer blockchain technology. With the support of the financial Cobb–Douglas algorithm, we can know that the economy generated by the financial industry occupies an important position in our country's national economy. The financial industry is related to our country's economic development and social stability. It has the functions of optimizing capital allocation, adjusting, reflecting, and supervising the process of economic growth. However, the development of our country's financial industry still implements a separate operation and management system, and business control is relatively strict. Therefore, the development trend of our country's financial industry is bound to be technological. While developing Internet finance, it is necessary to further improve the operating system of financial institutions, improve the core competitiveness of financial companies in foreign and global financial markets, and establish their own financial characteristics. Cultivate high-quality financial talents and jointly promote the rapid development of China's financial industry.

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11 Financial Efficiency Differentiation Based on Data Quantitative Analysis under Big Data Technology

Yichen Song

1 Introduction

As the blood of economic development, finance plays an irreplaceable role in activating the economy [1,2]. First, it plays a role in accelerating the accumulation and concentration of capital, making it possible to expand the scale of the economy. Second, it plays a role of conduit, connecting the capital surplus with the capital demanders. Third, it improves the utilization efficiency of resources, and allocates resources to efficient users, So that social resources can be reasonably allocated [3,4]. The level of financial development is measured by the rational use of financial resources. Only by achieving the unity of the quantity and quality of financial resources can we achieve the sustainable development of finance [5,6]. At present, our country is still in the ranks of developing countries, so it is imperative to improve the financial system and improve financial efficiency (FE). China has a vast territory, and the phenomenon of unbalanced economic development can be seen everywhere. However, with the economic development of finance, there are also regional differences in China [7,8]. What is the relationship between financial regional differences and economic regional differences and how to promote the balanced development of the regional economy by optimizing regional FE has become a topic of concern [9,10]?

In the research of regional FE differentiation, many scholars at home and abroad have studied it and achieved good results. Hu J, Li g, and Zhu f use the regional difference index of FE to make a regression analysis on the regional economic development index. The conclusion is that there is a significant positive correlation between regional FE difference and economic development difference, and the regression coefficient of FE difference to economic development difference is greater than 1, which indicates that FE difference is a very important factor affecting economic difference [11]. Kring w n and Grimes w w w use the per capita GDP growth rate as the explained variable to conduct a regression analysis to explain the financial correlation rate. The research shows that there is a close relationship between economic growth and FE in different regions of China, FE is conducive to economic

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growth, and the difference in FE in China can partly explain the difference in regional economic growth in China [12].

This chapter mainly studies the difference between FE in China's coastal areas from the perspective of FE differentiation and mainly selects Tianjin, Hebei, Shanghai, Liaoning, and Shandong to analyze the difference of FE in China's coastal areas, and studies the difference between FE among coastal areas. Based on the big data technology, this chapter collects the FE data of these five coastal cities, and then studies the FE data of China's coastal areas through the data quantitative analysis method. By selecting the FE data of China's coastal provinces over the years to calculate their average value, this chapter studies the changing trend of FE among coastal areas.

2 Regional FE Differentiation

2.1 Influencing Factors of FE Differentiation

1 Economic factors

Finance is the product of economic development to a certain stage, and finance ultimately serves the economy. The level of economic development plays an important role in the development of the regional financial ecosystem and the coordinated development of regional finance. The level of regional economic development has an impact on the financial market, financial instruments, and financial institutions of the regional financial industry, and this impact plays an important role in the operation efficiency of the regional financial system. The development of the regional economy promotes the development of the financial industry, improves the relevant systems in the financial field, and improves the operation ability of the regional financial ecosystem. With the continuous improvement of the level of economic development, on the one hand, it can promote the scale of the financial sector, improve the requirements of the financial sector, and then improve the operational efficiency of the financial industry; on the other hand, with the improvement of the level of economic development, the scale of non-performing assets in the financial ecosystem can be effectively controlled, so as to improve the operational efficiency.

The upgrading of industrial structure and the development of emerging industries will change the existing financial demand and have higher requirements for related finance, so as to improve the level of FE and promote financial development. The mechanism of industrial structure on regional FE is as follows: first, the organization and scale of the industry promote the saving of means of production and reduce the production cost of enterprises; second, when the production scale of an enterprise reaches a certain level, it will promote the transformation of the enterprise, abandon the original inefficient production tools, and use advanced machines for production, so as to improve the production efficiency of the enterprise Thirdly, when the scale of industrial organization reaches a certain degree, it will accelerate the formation of division of labor and cooperation between different regions, which will play a certain role in reducing the operation and management costs of enterprises, so as to further improve the labor productivity of enterprises; fourthly, when the industrial structure between different regions is rationalized, it will promote the regional economic development on different spatial scales The growth of FE between economies shows a more coordinated and balanced trend, which ultimately plays a role in promoting the improvement of regional FE.

2 Financial influencing factors

Financial agglomeration refers to the spatial concentration of financial industry and corresponding economic activities in a region, which attracts peripheral financial activities to the central city. Financial agglomeration will improve the financial development level and efficiency level of the agglomeration area, and the financial agglomeration of the central city will also have a financial radiation effect on the surrounding cities, promoting the financial development and efficiency level of the surrounding cities. Industrial spatial agglomeration has corresponding advantages. Industrial spatial agglomeration promotes the continuous development of professional investment and service level, provides a suitable place for professional skilled workers to exchange and learn, and also enables enterprises to benefit from technology spillover. However, we should also note that if the degree of agglomeration is excessive, it will lead to the uneconomic phenomenon of agglomeration. Because the existence of economies of scale will make the existing economy continue to grow, but when the scale reaches a certain extent, there will be a scale diseconomy phenomenon, at this time, the advantage of unit product cost reduction disappears, and then lose the benefits of economies of scale.

3 Political influence factors

The market mechanism has higher economic efficiency because the market economy plays an important role in the optimal allocation of social resources. But the market will also fail, and at this time the government's appropriate intervention in the economy has played an important role. However, excessive government intervention will have a negative impact on the economy. The mechanism of government intervention in regional finance is: when market failure occurs, appropriate government intervention in the market is conducive to the optimal allocation of market financial resources. However, due to the particularity of China's financial market, the government has carried out more regulation and intervention in China's financial market, which has a great impact on the healthy development of the financial market and seriously affected the operational efficiency of China's financial market.

2.2 FE in Regional Economic Development

1 Conducive to capital accumulation

The rapid development of the regional economy needs a lot of capital support. The success of regional economic development depends on the smooth formation of capital. In the beginning, the regional financial system departments increased the accumulation of capital by expanding the scale, forming economies of scale, and mobilizing regional idle funds, so as to increase the total marginal savings. Secondly, reduce the transaction cost of the financial sector, the financial sector can increase the liquidity of the market through the innovation of financial products, and can improve the savings motivation of investors. Finally, the profitability and risk of financial institutions can reduce the holding of current assets by improving the management level, so as to increase the proportion of regional production capital investment. Therefore, through the play of financial functions, idle funds in the market can be efficiently converted into capital, providing strong capital support for the development of the regional economy.

2 Promote the upgrading and optimization of industrial structure

If the regional economy wants to develop rapidly, technological progress and industrial upgrading are the keys, and the upgrading of the industrial structure needs technical support. Technology may have less demand for finance in the R & D stage, but it needs a lot of financial support in the technology implementation stage. There is a great risk in the stage of technology transforming into productivity, and few capital suppliers are willing to provide a lot of funds for it. If the finance is more developed, then the concept of risk management is more mature, which can provide funds for the transformation of technology to productivity, accelerate the upgrading of regional industrial structure, and promote the rapid development of the regional economy.

3 Capital flow-oriented mechanism

The growth of the regional economy not only needs a lot of capital support but also needs a reasonable allocation of savings resources, so that resources and investment structure can achieve harmony. The quality of investment is more important than the quantity of investment. Only by reducing inefficient investment can the regional economy maintain stable growth. An efficient financial system can integrate the decentralized capital market, which will promote the reallocation of capital in the whole region. The financial system can use its information advantage to guide the capital flow to those investment fields or industries with high efficiency, relatively low risk, and great development potential, so as to improve the efficiency of capital use. Finally, through financial resources to achieve the optimal allocation of the regional capital, so as to promote regional economic stability and sustainable development.

2.3 Suggestions for Improving FE Differentiation

1 Building a stable economic environment

Economic development is the foundation of financial development, and sound macroeconomic environment and policies have played a supporting role in the supervision of the regional financial industry in coastal areas. In the empirical analysis of the influencing factors of FE in coastal areas, the level of economic development and the optimization of the industrial structure have a significant positive role in promoting the regional FE. Governments at all levels should firmly grasp the dividend of economic development and industrial structure optimization, continue to improve the economic level in the process of regional development, and improve the comprehensive strength of the economy; at the same time, constantly improve the competitiveness of the economy, optimize the industrial structure, expand the proportion of the tertiary industry in the development of the national economy; the upgrading of industrial structure, the development of emerging industries will make the existing financial demand change, produce higher requirements for related finance, and then improve the level of FE. At the same time, we should speed up the degree of economic openness, actively introduce rich foreign capital investment, advanced management experience, and technical level in the process of opening up, and fully grasp the role of economic openness in promoting regional FE. Governments at all levels should build a stable macroeconomic environment, reduce the interference of future uncertainty on the economy, promote the steady growth of the macro-economy, and ultimately promote the development of the financial industry.

2 Reducing excessive government intervention

From the perspective of political factors, excessive government intervention has seriously affected the improvement of regional FE in coastal areas. The empirical results also show that government intervention has a significant negative effect on the improvement of efficiency. This is mainly due to the government's intervention in the regional financial industry, which affects the free allocation of the regional financial resources market, and then reduces the operational efficiency of the regional financial market. In view of the current situation of the development of the regional financial industry in Beijing's coastal areas, governments at all levels should adjust to the following aspects. First, we should constantly accelerate the reform of government institutions and administration, restrict the administrative power of the government, and realize the pattern of "small government, big society". Second, establish and improve the property rights protection and the basic institutional framework of the rule of law and transparency, realize the free competition pattern of the market, and eliminate the obstacles of vested interest groups to the development of regional finance; third, continuously speed up the reform of the existing monopoly industries, eliminate the local protectionism in various regions and the administrative intervention of governments at all levels, gradually relax the control of finance, and let the market more Field adjustment and configuration.

3 Building a perfect regional financial cooperation mechanism

From the perspective of financial factors, the coordinated development of regional finance in coastal areas requires financial institutions to provide financial service products to meet the market demand. However, due to the limitations of China's financial policy and administrative supervision, financial institutions are unable to carry out the above services in an all-round way. Therefore, at present, we should break the original supervision mode, conform to the needs of the times and development, and establish a healthy financial system Full cooperation mechanism. We should abolish the original mode of strictly dividing the scope of administrative supervision according to administrative divisions, coordinate the relationship between regional development, and reduce the cost of information dissemination and flow. When designing and planning the regional financial cooperation mechanism, in order to effectively improve the efficiency of cooperation, we should focus on the following two aspects: first, to build a fair principle of interest coordination, so that all financial partners can get the normal interests they deserve; second, to build an effective information sharing platform, so as to provide the necessary system for the orderly promotion of regional financial cooperation Guarantee, and ultimately achieve the efficient use of financial resources in the whole region.

2.4 Algorithm Model of FE Analysis

1 Malmquist exponential decomposition model

Malmquist index reflects the change of TFP by measuring the distance between the production decision-making unit and the production frontier. By comparing the best frontier with the actual production surface of each production decision unit, the Tfpc change of each production decision unit is obtained. According to the application demand of FE, the algorithm of TFPC is as follows:

$$M_0 = (x^{t+1}, y^{t+1}, x^t, y^t) = TFPC = \sqrt{\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}} * \sqrt{\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}}$$
$$= \text{EFFCH} * \text{TECH}$$

When TECH < 1, it indicates that the efficiency is backward, while when TECH > 1, it indicates that the efficiency has been improved significantly. Financial allocation efficiency is mainly financial allocation efficiency effch and financial innovation efficiency tech. The decomposition of FE into financial allocation efficiency and financial innovation efficiency is helpful for us to deeply study the channels and degree of influencing FE, which is convenient for centralized research and analysis.

2 Theil index model

The common methods to compare regional differences are the Gini coefficient, Theil index, coefficient of variation, and so on. In this chapter, the Theil index is used to measure the difference between pure technical efficiency and scale efficiency, and the Theil index is decomposed into intra-regional and inter-regional differences, the algorithm is as follows:

$$T_w = \sum_{K=1}^{m} f_K \frac{U_K}{U} T(Z^K), T_b = \sum_{K=1}^{m} f_K \frac{U_K}{U} \ln \frac{U_K}{U} \tag{2}$$

3 Experimental Study

3.1 Subjects

In order to explore the differences of FE in China's coastal areas under the big data technology, this chapter takes China's coastal areas as the research object, uses the Malmquist model and Theil index as the model algorithm analysis, selects Tian jin, He bei, Shang hai, Liao ning, and Shandong as the representative coastal areas, studies the differences of FE in China's coastal areas, and explores the differences of FE among different region differences.

3.2 Experimental Method and Steps

Based on the literature review, this chapter analyzes the differences between FE in China's coastal areas. This chapter selects representatives of Tianjin, Hebei, Shanghai, Liaoning, and Shandong to analyze the financial allocation efficiency, financial innovation efficiency, financial scale efficiency, and financial technology efficiency of these five regions by using the Malmquist index and Theil index and then analyzes the FE data of China's coastal areas through data quantitative analysis method to study the differences among the coastal areas. This chapter explores the relationship between FE and economic, financial, and political factors and puts forward reasonable suggestions to improve the phenomenon of FE differentiation.

4 Experimental Research and Analysis

4.1 Malmquist Index in Coastal Areas

This chapter estimates the changes in FE in China's coastal areas in recent years by studying the Malmquist index and studies the changes in FE from a dynamic point of view. This chapter selects Tian jin, He bei, Shang hai, Liao ning, and Shan dong, five typical regional representatives in the coastal areas to analyze the changes in FE, and analyzes their financial allocation efficiency and financial innovation efficiency, so as to explore the development direction The FE of these regions is shown in Table 11.1.

From Figure 11.1, we can see that the financial allocation efficiency of Tianjin and Liaoning is significantly higher than that of Hebei, Shanghai, and Shandong provinces. It can be seen that Tianjin Liaoning has high efficiency in financial allocation and FE has been improved. From the perspective of financial innovation efficiency, Shanghai has the highest efficiency, which is also due to the rapid renewal of financial innovation in Shanghai, as the most prosperous area of import and export trade.

Table 11.1 Regional Malmquist index analysis

Province	*EFFCH*	*TECH*
Tianjin	1.028	0.974
Hebei	1.002	0.969
Shanghai	0.993	0.985
Liao ning	1.025	0.936
Shandong	0.992	0.908

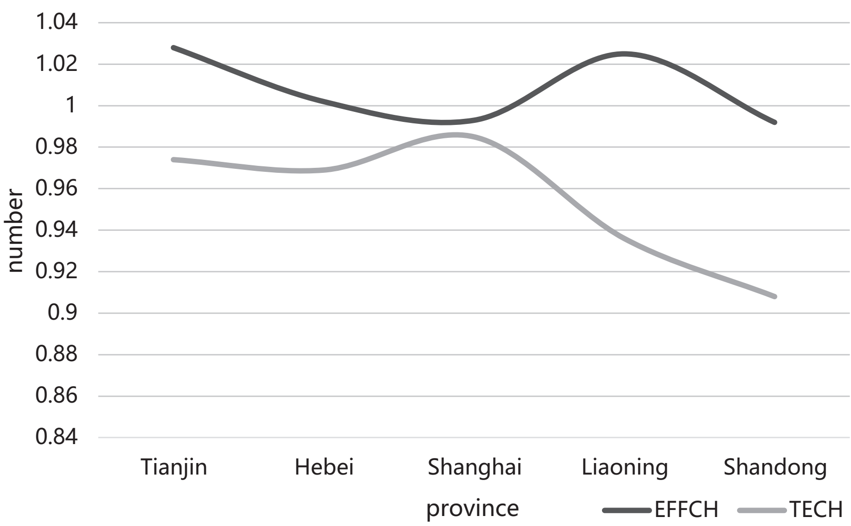

Figure 11.1 Regional Malmquist index analysis.

4.2 Research and Analysis of Theil Index

The Theil index is an indicator to measure the income gap between regions. In this chapter, we use the Theil index to study the differences between financial scale efficiency and financial technical efficiency among regions. We still select Tianjin, Hebei, Shanghai, Liaoning, and Shandong as the five coastal areas to decompose the five Theil indexes and study the regional differences. The results are shown in Table 11.2.

From Figure 11.2, we can see that there is also a large gap between cities in coastal areas of China, and there are differences in the efficiency of financial scale and financial technology between provinces. Tianjin's financial scale efficiency and technical efficiency are both higher than that of Shanghai, which also shows that the level of economic development is not the only factor determining FE.

5 Conclusions

The results show that the overall level of FE in China's coastal areas is average, the improvement of FE is slow, and the regional differences in FE in

Table 11.2 Comparative analysis of Theil index in different regions

Province	*Financial scale efficiency*	*Financial technical efficiency*
Tianjin	0.972	1.723
Hebei	0.965	0.986
Shanghai	0.774	1.147
Liaoning	0.958	1.433
Shandong	0.823	1.327

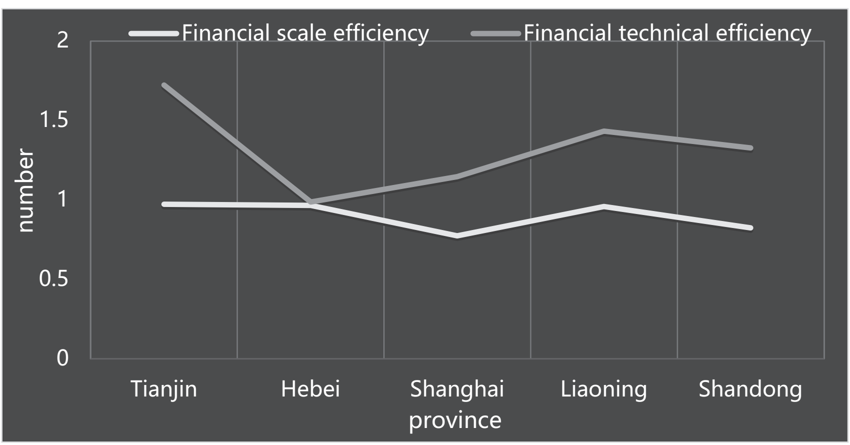

Figure 11.2 Comparative analysis of Theil index in different regions.

coastal areas are obvious. Based on big data technology, this chapter studies the FE differentiation of China's coastal areas from the perspective of FE differentiation. This chapter selects representatives of Tianjin, He bei, Shang hai, Liao ning, and Shan dong to analyze the financial allocation efficiency, financial innovation efficiency, financial scale efficiency, and financial technology efficiency of these five regions by using the Malmquist index and Theil index, and then analyzes the FE data of China's coastal areas through data quantitative analysis method to study the differences among the coastal areas This chapter explores the relationship between FE and economic, financial, and political factors and puts forward reasonable suggestions to improve the phenomenon of FE differentiation.

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12 Optimization algorithms for multiple-asset portfolios with machine learning techniques

Practical applications with forecasting of optimum and coherent economic capital structures

Mazin A. M. Al Janabi

1 Introduction

In this chapter, we characterize the trading risk for emerging equity markets by using a multivariate liquidity-adjusted value at risk (L-VaR) technique and optimization algorithms that focus on the modeling of optimum L-VaR under the notion of illiquid and adverse market conditions and by exercising different dependence measures (correlation factors) and liquidity closeout periods.[1] The overall aim of this chapter is to construct different structured equity portfolios, which includes stock markets indices of the Gulf Cooperation Council (GCC) region, and to evaluate the risk characteristics of those portfolios besides examining a robust iterative optimization algorithmic process for computing efficient and coherent[2] economic capital.[3] To that end, we apply a general trading risk modeling algorithm that accounts for the characteristics of the series of equity price returns—for example, fat tails (leptokurtosis), skewness, correlation parameters, and closeout horizons—and effectively forecasts market risk within a short time horizon. As such, the robust modeling technique and non-linear quadratic optimization algorithms implemented in this chapter are based on the Al Janabi model (Al Janabi, 2008; Madoroba and Kruger, 2014).

In spite of the increasing importance of the GCC financial markets, there is very little published research in this respect and particularly within the context of a comprehensive testing of the GCC stock market risk-return characteristics and dynamic economic capital allocation with advanced quantitative risk measures. The literature on testing volatility, expected returns, and risk management of the GCC equity markets has been relatively meager, inconclusive, and providing mixed results. As such, and in contrast to all existing published literature pertaining to the application of advanced quantitative risk-return empirical examination and dynamic economic capital allocation, this chapter intends to make the following main contributions to the academic literature in this specific risk management

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and portfolio optimization fields. Firstly, it represents one of the limited numbers of research studies that empirically examine the equity-trading risk management using actual data of the GCC financial markets. Secondly, a database of the daily indices of the GCC stock markets is utilized whose behavior is presumably more diverse than if equity assets of any particular stock market had been employed, as other authors have done heretofore. The basic argument is that specific country indices may have, compared to individual stocks, a more predictable structure due to aggregation. Thirdly, unlike most empirical studies in this field, this chapter employs a robust trading risk management modeling algorithm that considers risk testing and analysis under normal (regular), severe (crisis), and illiquid market outlooks. The principal advantage of employing such a model is the ability to capture a full picture of possible loss scenarios of actual equity-trading portfolios. Fourthly, this chapter implements a novel approach to optimum (efficient) economic capital allocation besides a robust optimization algorithm for the selection of efficient and coherent economic capital portfolios within an L-VaR framework. To that end, an L-VaR modeling algorithm is introduced to allocate equity assets by minimizing economic capital subject to the application of meaningful operational and financial constraints. The focus on L-VaR as the appropriate measure of portfolio risk allows risk managers and portfolio managers to assign the desired liquidity horizon and to allocate long- and short-sale and long-only trading assets and to determine economic capital according to realistic market trading environments. In this sense, the current work is closer to the real behavior of portfolio managers who employ, in some pertinent way, active and dynamic asset allocation trading strategies with the objective of minimizing the amount of economic capital. To the present authors' knowledge, very few studies have done this type of empirical testing and analysis. Another contribution of the chapter is to implement an innovative optimization algorithm to estimate the portfolio manager's risk parameters that eventually leads to the estimation of optimum economic capital and can have important uses and applications in machine learning and artificial intelligence, machine learning for the policymaking process, and the Internet of things (IoT). Accordingly, a robust optimization algorithm is used to compute risk tolerance in the L-VaR asset allocation model under the notion of different closeout horizons and correlation factors. We then demonstrate, by applying the liquidity risk measures to the GCC financial markets, to what extent the quantified liquidity trading risk effects can impact traditional measurement of market risk under the assumption the of different measures of dependence: i.e., empirical correlations, zero, 100% negative and 100% positive correlations. Finally, the obtained empirical results are interesting in terms of theory as well as practical applications and provide an incentive for further research in the area of L-VaR, economic capital, and equity price risk management. Moreover, the different optimization case analysis studies and discussions are widely applicable to any equity end-user, providing potential applications to practitioners and research ideas to academics.

2 Risk management in emerging GCC financial markets and Basel II and Basel III capital adequacy accords

In the last three decades, financial markets and institutions in emerging markets (such as in the case of the GCC financial markets) have greatly increased their holdings of trading assets, such as bonds, equities, interest rate and equity derivatives, foreign exchange, and commodity positions. Their intention in this has been to earn trading profits and to hedge exposures elsewhere in their trading portfolios. Nevertheless, the lack of adequate market risk measurement, management, and control tools and modeling techniques are some of the contributing factors that have led to major financial losses among national and multinational corporations in emerging economies.

To quantify the risks involved in their trading operations, major financial and non-financial institutions are increasingly exploiting VaR internal models. Since these institutions differ in their individual characteristics, tailor-made internal risk models are more appropriate. Moreover, the increase in the relative importance of trading risk has obliged regulators to reconsider the system of capital requirements as outlined in previous Basel committee capital accords. Fortunately, in accordance with the Basel II and Basel III capital adequacy accords, trading institutions are permitted to develop their own internal risk models for the purpose of providing adequate risk measures. Furthermore, internal risk models can be used in the determination of capital cushion that entities must hold to endorse their trading of securities. The benefit of such an approach is that it takes into consideration the relationship between various asset types and can accurately assess the overall risk for a whole combination of multiple-asset trading portfolios.

The Basel II and Basel III capital adequacy accords, for the establishment of effective internal models of risk management, have motivated several emerging countries to be part of the agreement at different implementation levels. This is aggravated by the fact that emerging markets financial institutions face a substantial competitive disadvantage if they are enforced to continue using the standardized Basel approach. As such, several emerging markets would like to be Basel II and Basel III compliant and hence are already in advanced steps to implement internal models and to comply with the Basel agreement. Basel II and Basel III's overall intention is to endorse adequate capitalization of banks and other financial institutions and encourage improvements in risk measurement, management, and control, thereby strengthening stability in the global financial system. Basel II and Basel III accords do so by implementing several-fold complementary pillars: (1) capital adequacy methodology and computation; (2) supervisory review; and (3) setting disclosure terms to enable market discipline; liquidity risk, stress testing, and scenario analysis in light of the aftermath of the 2007–2009 financial crunch[4].

As a result, a number of Arab countries have joined the implementation of modified versions of the Basel II and Basel III capital adequacy accords. In fact, the GCC financial markets, in general, are in the progressive stages of implementing advanced quantitative risk management regulations and techniques. Furthermore, in recent years outstanding progress has been done in cultivating the culture of risk management among local financial entities and regulatory institutions. In the Middle East, the majority of banking assets are expected to be covered by Basel III regulations during the 2020–2021 period. Generally speaking, capital ratios are fairly strong in the GCC region, though they have fallen lately as banks have expanded their products and operations. Within the GCC, there have been negotiations for a common application of the Basel II and Basel III rules, though with different timeframes. This is because some GCC countries are more diverse, for instance, in terms of the presence of foreign banks than others (Al Janabi, 2013, 2014).

The financial industry in the GCC zone is generally sound, and the six countries continue to develop their financial system to attract more foreign portfolio investors and to expand the opening of its financial system to the exterior world. Consequently, several local financial institutions are in a consolidation route; and some others have already followed a process of convergence of their financial operations and have started the procedure of modernizing their internal risk management capabilities. By the standards of emerging market countries, the quality of banking supervision in the six states of the GCC is well above average. Despite the latest progress in the GCC financial markets to become Basel II and Basel III-compliant countries, in the midst of the 2007–2009 market turbulences and its aftermaths it has been deemed necessary (by local regulatory authorities) to adapt proper internal risk models, rules and procedures that financial entities, regulators and policymakers should consider in developing their daily trading risk management objectives and to determine optimum economic capital allocations effectively (Al Janabi, 2013, 2014).

In this background, trading risk management has become an important theme in emerging illiquid markets, such as in the case of the GCC financial markets. Accordingly, the goals of this research study are to demonstrate the necessary analytical steps and internal risk management processes that a market's participants (market-makers or portfolio managers) can need in their day-to-day positions' taking. This chapter implements real-world risk management modeling techniques and optimization strategies that can be applied to equity-trading portfolios in emerging markets, such as, in the context of the GCC financial markets. This is with the objective of developing the basis of robust financial modeling techniques for the computation, management, and control of risk exposures in the day-to-day trading operations. Analytical procedures that are discussed in this chapter can aid financial markets' participants, regulators, and policymakers in founding contemporary and sound internal quantitative risk management modeling methods to handle equity-trading risk exposures.

Despite the increasing importance of trading risk management, published research in this specific risk management area is slow to emerge and specifically from the perspective of market practitioners. In particular, the main aim of this chapter is to fill a gap in the equity risk management literature (especially from the perspectives of emerging illiquid markets) and to bridge the disparity between the academic and professional finance communities. This chapter makes use of robust risk management methodologies and modeling techniques that can be applied to equity multiple-asset portfolio investments and to day-to-day equity-trading activities in emerging markets. In this work, key risk management methods and optimization techniques that financial entities, regulators, and policymakers should consider in developing their daily equity-trading risk management objectives are examined and adapted to the specific needs of emerging illiquid markets, such as in the context of the GCC stock markets. The suggested quantitative modeling methods can be implemented in almost all emerging economies if they are adapted to correspond to each market's initial level of sophistication. Similarly, it can aid in the progress of regulatory technology (RegTech) for the global financial services industry and can be of interest to professionals, regulators, and researchers working in the field of financial engineering and FinTech; and for those who want to advance their understanding of the impact of innovative risk computational techniques and reporting processes on regulatory challenges for the financial services industry and its effects on global financial stability. In addition, it provides key real-world implications for portfolio and risk managers, treasury directors, risk management executives, policymakers, and financial regulators to comply with the requirements of Basel III best practices on liquidly risk and capital adequacy[5].

2.1 Foundation and objective of current research

Equity prices are exposed to a variety of volatile market risk factors that can be and have been examined in a portfolio context. However, despite the rising interest in emerging markets, as in the case of the GCC financial markets, earlier research does not provide any robust methods for handling trading risk and coherent assessment of economic capital allocation under illiquid and adverse market settings, particularly within emerging markets equity-trading portfolios. Considering the recent interest in L-VaR and the variability of the market risk factors of different emerging markets, the overall aim of this chapter is to examine L-VaR and economic capital me asures in the context of equity-trading portfolios (of either long-only positions or combinations of long- and short-sale trading positions) and under the notion of different dependence measures (correlation factors) and liquidity horizons. In particular, this chapter develops and tests L-VaR and economic capital measures, using several alternative strategies in predicting large losses, with the aid of different liquidation horizons and under a pre-determined confidence level. Thus, equity-trading portfolios provide a practical optimization case study for testing L-VaR and economic capital methodologies in the prospect of equity prices, helping to establish the appropriateness of L-VaR as a viable and important risk management tool for equity risk managers and portfolio managers.

Irrespective of the growing standing of the GCC financial markets, there is very little published research in this respect, primarily within the liquidity trading risk management context. Moreover, to the best of our knowledge, there are very few published research papers in the international literature on liquidity risk management and coherent economic capital allocation that takes into account the GCC countries as an optimization case study in advanced portfolio management and risk management applications. As such, this chapter aims to implement robust modeling techniques for the computation of liquidity risk and to show certain practical applications of L-VaR for the assessment of coherent economic capital structures. In contrast to all existing published literature pertaining to the application of L-VaR and economic capital methods, this chapter implements robust modeling techniques with a closed-form parametric L-VaR in the case of emerging financial markets.

This research study is one of very few known attempts at empirically examining the performance of L-VaR and economic capital measures in the framework of a diverse equity portfolio, using the modeling algorithms and optimization techniques of the Al Janabi model (Al Janabi, 2008; Madoroba and Kruger, 2014). To date, all known empirical studies examining the performance of alternative L-VaR measures have been conducted in the framework of portfolios containing foreign exchange, interest rate, or equity data with portfolios often developed arbitrarily. The equity indices selected for this research study provide a realistic alternative portfolio, as well as new data, for studying existing techniques of L-VaR estimation. This research study makes advances in understanding L-VaR and coherent economic capital assessment techniques and their performance in the context of equity price risk management. The results of this research study also provide an incentive for further research in the area of L-VaR, economic capital and equity price risk management.

This chapter shows that the performance of efficient and coherent economic capital portfolios depends on the expected returns, individual L-VaR positions, liquidity horizons of each trading asset, and the set of portfolio weights. The empirical findings indicate that the risk tolerance in the L-VaR framework is time-varying and closely related to the selection of the unwinding liquidity horizons and expected returns, in addition, to the impact of the assumed correlation factors of the portfolio. Moreover, in this work, the relative performance of L-VaR and the economic capital selection model is compared in a dynamic asset allocation framework. The goal of the dynamic asset allocation is to find the optimum equity asset allocation mix by minimizing the objective function of L-VaR and economic capital subject to the imposition of certain realistic operational and financial constraints based on fundamental asset management considerations.

The empirical analyses are provided using a daily database of the GCC stock markets for the period 2004–2009, which falls within the most severe part of the 2007–2009 global financial crisis. Dataset of stock market indices is gathered, filtered, and processed in such a manner so that to create meaningful quantitative testing and examination of equity market risk exposure. Several empirical optimization case studies are carried out with the objective of assessing L-VaR and economic capital under diverse illiquid market outlooks. The L-VaR and economic capital estimations have been obtained for various equity-trading portfolios in the GCC stock markets through the implementation of a modified closed-form parametric L-VaR optimization algorithm, where conditional volatilities and expected returns are estimated with the aid of a generalized autoregressive conditional heteroscedasticity in mean [GARCH-M (1,1)] model. The empirical testing results are then used to draw conclusions about the relative liquidity of the different equity indices and the importance of liquidity risk in L-VaR and economic capital assessment. The results indicate that our modeling techniques perform better than the standard mean-variance VaR modeling method in terms of the optimum portfolio selection process as well as in determining coherent economic capital portfolios. The empirical findings are persistent over the entire sample period and robust across alternative investment horizons.

The modeling techniques, optimization algorithms, and empirical results are interesting in terms of theory as well as practical applications and can have many uses and applications in financial markets, particularly in light of the 2007–2009 global financial meltdown. In addition, the implemented optimization techniques and risk assessment algorithms can aid in advancing risk management practices in emerging markets, particularly in light of the 2007–2009 financial turmoil. Similarly, it can aid in the progress of RegTech for the global financial services industry and can be of interest to professionals, regulators, and researchers working in the field of financial engineering, machine learning for the policymaking process, FinTech, and machine learning techniques for the IoT data analytics; and for those who want to advance their understanding of the impact of innovative risk computational techniques and reporting processes on regulatory challenges for the financial services industry and its effects on global financial stability. Furthermore, it provides key real-world implications for portfolio/risk managers, treasury directors, risk management executives, policymakers, and financial regulators to comply with the requirements of Basel III best practices on liquidly risk and capital adequacy.

The balance of the chapter proceeds as follows. Section 3 demonstrates, by applying the L-VaR modeling techniques and optimization algorithms to the GCC equity markets, to what extent the quantified liquidity effects can affect the conventional assessment of equity-trading risk and optimum economic capital allocation. In addition, this section examines the overall results of the different empirical tests and discusses the process and infrastructure that support large-scale quantitative-based investing and the role of an optimization engine in this process. This section also reflects on the construction of efficient and coherent economic capital portfolios, first by describing a simple investment objective that an equity portfolio manager may seek to optimize and second by implementing different combinations of both long-only and long/short-sale equity-trading strategies. The discussion then turns to the inputs of the portfolio construction process such as trading budget constraints. Section 4 concludes the chapter.

3 Forecasting of the risk exposure for dynamic economic capital portfolios using machine learning algorithms

In this chapter, data on the daily return of the GCC stock market key indicators are filtered and adapted for the design of relevant inputs for the computation of all risk parameters. As such, historical data (of more than 6 years) of daily closing index levels, for the period 17/10/2004–22/05/2009, are obtained for the purpose of carrying out this empirical study and for the construction of market and liquidity risk management algorithms. The historical data are drawn from Reuters 3000 Xtra Hosted Terminal Platform and Thomson's Datastream datasets, and it falls within the severe part of the 2007–2009 global financial crisis. The total numbers of indices that are considered in this work are nine; seven local indices for the six GCC stock markets (including two indices for the UAE markets) and two benchmark indices, detailed as follows:

- DFM General Index (United Arab Emirates, Dubai Financial Market General Index)
- ADSM Index (United Arab Emirates, Abu Dhabi Stock Market Index)
- BA All Share Index (Bahrain, All Share Stock Market Index)
- KSE General Index (Kuwait, Stock Exchange General Index)
- MSM30 Index (Oman, Muscat Stock Market Index)
- DSM20 Index (Qatar, Doha Stock Market General Index)
- SE All Share Index (Saudi Arabia, All Share Stock Market Index)
- Shuaa GCC Index (Shuaa Capital, GCC Stock Markets Benchmark Index)
- Shuaa Arab Index (Shuaa Capital, Arab Stock Markets Benchmark Index)

Moreover, in this work index returns are defined as $R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1})$, where $R_{i,t}$ is the daily return of index i, ln is the natural logarithm, $P_{i,t}$ is the current level of index i, and $P_{i,t-1}$ is the previous day index level. Furthermore, for this particular research study, we have chosen a confidence interval of 95% (or 97.5% with a "one-tailed" loss side) and several closeout horizons to compute L-VaR under normal and stressed (severe) market outlooks.[6] In the process of examining the data, firstly, the daily log-returns of the nine indices have been computed. These daily returns are essential inputs for the calculation of conditional volatilities, expected returns, correlation matrices, systematic risk parameters (or beta factors), skewness, kurtosis and to perform the Jarque–Bera (*JB*) test of non-normality. An iterative optimization algorithm software is programmed/coded for generating trading portfolios and consequently for carrying out L-VaR and economic capital scenario analysis under extreme illiquid market conditions and by implementing different dependence measures. The examination of data and discussion of empirical results are organized and explained as follows:

3.1 Statistical analysis of conditional volatility and testing for the asymmetric distribution of returns

To examine the relationship between the expected returns and volatility of stock market indices, we implement a conditional volatility method to determine the risk parameters that are needed for the L-VaR's risk engine and thereafter for the estimation of daily market liquidity risk exposures and economic capital requirements. Indeed, the time-varying pattern of stock market volatility has been widely recognized and modeled as a conditional variance within the GARCH-M (1,1) framework, as originally developed by Engle (1982, 1995).

To that end, Table 12.1 illustrates the daily conditional volatility of each stock market under normal and severe[7] (crisis) market conditions and by implementing the GARCH-M (1,1) model. Severe market conditional volatilities are calculated by implementing an empirical distribution of the time series past returns for all stock market indices and, hence, the maximum negative returns (i.e., losses or downside risk), which are witnessed in the expected return time series, are selected for this purpose. This downside risk tactic can aid in overcoming some of the limitations of the normality assumption and provide a better analysis of L-VaR and coherent assessment of economic capital allocation, especially under severe and illiquid market outlooks.

From Table 12.1 it is apparent that the index with the highest volatility is the SE All Share Index under normal market conditions, whereas the DFM General Index demonstrates the highest volatility under severe market conditions. Annualized volatilities are depicted in Table 12.1, and this is performed by adjusting the daily conditional volatilities with the square root of 260—assuming there are 260 trading days in the calendar year. An interesting outcome of the study of systematic risk (beta sensitivity risk factors) is the manner in which the results are varied across the sample indices as shown in Table 12.1. SE All Share Index appears to have the highest

Table 12.1 Risk analysis dataset: daily and annual volatility and sensitivity factor

Stock market indices	*Daily volatility (normal market)**	*Daily volatility (severe market)**	*Annual volatility (normal market)**	*Annual volatility (severe market)**	*Sensitivity factor*
DFM General Index	1.81%	12.2%	29.2%	196.0%	0.58
ADSM Index	1.32%	7.1%	21.4%	114.1%	0.40
BA All Share Index	0.58%	3.8%	9.4%	60.8%	0.06
KSE General Index	0.71%	3.7%	11.5%	60.2%	0.14
MSM30 Index	0.79%	8.7%	12.8%	140.3%	0.10
DSM20 Index	1.48%	8.1%	23.9%	130.2%	0.31
SE All Share Index	1.86%	11.0%	30.0%	177.9%	0.98
Shuaa GCC Index	1.30%	8.1%	20.9%	130.6%	1.05
Shuaa Arab Index	1.15%	7.6%	18.5%	122.1%	1.00

Note: Asterisk * denotes estimation of conditional volatility using the GARCH-M model
Source: Designed by the author using in-house built algorithms and software.

systematic risk factor (0.98) vis-à-vis the Shuaa Arab Index, and the BA All Share Index seems to have the lowest beta factor (0.06). Moreover, in accordance with general belief, the Shuaa GCC Index (with a systematic risk factor of 1.05) is the one that seems to move very closely with respect to the benchmark Shuaa Arab Index.

In another research study, descriptive statistical analysis and tests of non-normality (i.e., asymmetrical distribution) are performed on the sample indices. To consider the distributional anomalies of asset returns, tests of non-normality are conducted on the equity indices using the *JB* test. In the first study, the measurement of skewness is done on the equity indices and the results are depicted in Table 12.2. It is seen that all indices show asymmetric behavior, between both positive and negative values. Moreover, kurtosis studies show similar patterns of abnormality (i.e., peaked distributions). At the upper extreme, MSM30 Index shows a big negative skewness (−0.57), which is combined with a very high Kurtosis—i.e., peakedness of (18.40). At the same time, some indices, such as in the case of the DSM20 Index, show less abnormality pattern (i.e., skewness of −0.11 and kurtosis of 5.59, respectively). As evidenced in Table 12.2, the above results of general departure from normality are also confirmed with the *JB* test. Nonetheless, the *JB* test shows an obvious general deviation from normality and, thus, rejects the hypothesis that the returns time series of the GCC stock markets are normally distributed. The interesting outcome of this study suggests the necessity of combining L-VaR and economic capital appraisals—which

Table 12.2 Risk analysis dataset: descriptive statistics of daily returns, skewness, kurtosis, and Jarque–Bera test of normality

Stock market indices	*Maximum*	*Minimum*	*Arithmetic mean*	*Expected return**	*Skewness*	*Kurtosis*	*Jarque–Bera (JB) test*
DFM General Index	9.9%	−12.2%	0.12%	0.14%	0.01	7.86	955*
ADSM Index	6.6%	−7.1%	0.07%	0.07%	0.12	7.26	734*
BA All Share Index	3.6%	−3.8%	0.05%	0.04%	0.43	10.24	2142*
KSE General Index	5.0%	−3.7%	0.09%	0.08%	−0.18	8.38	1173*
MSM30 Index	5.2%	−8.7%	0.12%	0.10%	−0.57	18.40	9617*
DSM20 Index	6.2%	−8.1%	0.06%	0.07%	−0.11	5.59	273*
SE All Share Index	9.4%	−11.0%	0.03%	0.01%	−0.97	8.47	1361*
Shuaa GCC Index	11.1%	−8.1%	0.06%	0.08%	−0.66	14.00	4949*
Shuaa Arab Index	9.4%	−7.6%	0.07%	0.10%	−0.61	13.79	4758*

Notes: Asterisk * denotes estimation of expected return using the GARCH-M model.
Source: Designed by the author using in-house built algorithms and software.

assume normal distributions of returns—with other methods such as stress testing and scenario analysis to get detailed perspectives of the other remaining risks (i.e., the fat-tails in the probability distribution) that cannot be captured with the simple assumption of normality.

3.2 Empirical analysis of different dependence measures for the L-VaR modeling algorithms

In this study, four different matrices of correlations parameters are used for the computation of L-VaR and economic capital allocation, namely $\rho = 1, -1, 0$, and empirical correlations. The objective here is to develop the necessary infrastructure for advanced quantitative risk analysis that will follow shortly. The rationality behind using the upper limits of extreme correlations, of $\rho = 1$ and $\rho = -1$, is to show the impact of extreme events on the computation of L-VaR when the dependence measure increases dramatically or switch signs under adverse market outlooks. For the empirical correlation case, the assembled correlation matrix is depicted in Table 12.3. This correlation matrix along with conditional volatility vectors are essential for the computation of L-VaR, stress-testing, efficient and coherent economic capital portfolios. As such, the results of Table 12.3 are integrated into the L-VaR's risk engine to estimate L-VaR parameters and economic capital requirements under the notion of different unwinding horizons and for both long-only and long/short-sale trading holdings.

Contrary to general belief, our analysis indicates that there are very small correlations between the GCC stock markets in the long-run horizon. Nonetheless, in the short-run period (or on a daily crisis basis), however, we found that correlations tend to increase in value (although not on a large scale) and it could even switch signs under certain circumstances.

These long-run low correlation associations are advantageous for investors who would like to hold a diversified equity portfolio in GCC countries, particularly for medium/long investment horizons. In general, it seems that the Saudi market, with correlation factors of 62% and 60% respectively, has the largest effect associated with the Shuaa GCC and Shuaa Arab indices. The Dubai and Abu Dhabi financial markets show a relatively moderate relationship of 56%, though they are located in the same country. Likewise, in accordance with general expectations, the Shuaa GCC and Shuaa Arab indices have shown a strong relationship of 93%.

3.3 Computation of economic capital with L-VaR modeling algorithms

In order to illustrate the linkage between the theoretical foundations of L-VaR and its practical application and value as a tool for equity-trading risk management, the simulation of different portfolios for the computation of economic capital is examined. These simulation case studies also

Table 12.3 Risk analysis data: correlation matrix of stock market indices

	DFM General Index	*ADSM Index*	*BA All Share Index*	*KSE General Index*	*MSM30 Index*	*DSM20 Index*	*SE All Share Index*	*Shuaa GCC Index*	*Shuaa Arab Index*
DFM General Index	100%								
ADSM Index	56%	100%							
BA All Share Index	12%	8%	100%						
KSE General Index	17%	16%	12%	100%					
MSM30 Index	12%	17%	11%	11%	100%				
DSM20 Index	18%	23%	12%	12%	20%	100%			
SE All Share Index	20%	20%	7%	16%	11%	10%	100%		
Shuaa GCC Index	37%	35%	13%	19%	13%	26%	62%	100%	
Shuaa Arab Index	39%	36%	12%	24%	15%	26%	60%	93%	100%

Source: Designed by the author using in-house built algorithms and software.

help in understanding the methods used in determining the performance of alternative economic capital estimation procedures in the context of equity-trading risk management.

Using the definition of economic capital, and under the assumption that a given equity portfolio has both long- and short-sale trading positions, Tables 12.4 and 12.5 illustrate practical risk simulation reports for the analysis of quantitative equity risk management activities. To that end, asset allocation and economic capital analysis are performed under the assumption that local indices represent exact replicas of diversified portfolios of domestic stocks for each GCC stock market respectively. Furthermore, all risk simulations are performed at the one-tailed 97.5% level of confidence over different closeout periods.

In these hypothetical risk simulation studies, the total portfolio value is AED10 million (UAE Dirham) and with different asset allocation ratios. The examination is carried out with one-day and ten-day liquidity horizons—i.e., one or ten days to unwind the entire equity assets. Furthermore, Tables 12.4 and 12.5 denote the effect of stress testing (i.e., economic capital under severe market outlooks) and the impact of different correlation factors on the computation of annual economic capital. The risk-engine economic capital report depicts also the overnight conditional volatilities using GARCH-M (1,1) model, in addition to their respective sensitivity factors and systematic beta risk factors. Crisis market daily volatilities (or downside-risk) are evaluated and illustrated in these reports too. These daily severe downside-risk volatilities represent the maximum losses, which are perceived in the historical time series, for all stock market indices. In essence, this approach can aid in overcoming some of the limitations of the normality assumption and provide a better analysis of economic capital, especially under severe and illiquid market settings. The effects of short sales (albeit short sales are currently not permitted in the GCC stock markets) are depicted in Tables 12.4 and 12.5 as well. One of the interesting results of this study is the way in which the economic capital statistics have decreased. These findings might be explained by the way in which the overall multi-assets portfolio is funded—in other words, long positions have been funded with short sales of other assets and, thus, have led to a reduction in the overall risk exposure. In fact, one of the principal advantages of computing L-VaR and economic capital with a matrix-algebra framework is the ability in which the effects of short sales can be incorporated without a tedious mathematical technique.

In this backdrop, the economic capital structure is computed under normal and severe market conditions by taking into consideration different correlation dynamics (i.e., empirical correlations, zero, −100%, and +100% correlations between the various risk factors). Under correlation +1, the assumption is for 100% positive relationships between all risk factors all the time, whereas for the zero-correlation case, there are no associations between all positions. While the −1 correlation case assumes 100% negative

Table 12.4 Economic capital analysis under different market conditions, full case study

Asset allocation and economic capital analysis

Stock market indices	Market value in AED	Asset allocation Percentage	Liquidity Holding Horizon	Daily volatility (Normal)	Daily volatility (severe)	Sensitivity factor	**Annual economic capital (EC) in million AED [normal market conditions]**			
DFM General Index	$ 6,000,000	60.0%	1	1.81%	12.16%	0.58				
ADSM Index	$ 4,000,000	40.0%	1	1.32%	7.08%	0.40	**ρ = Empirical**	**$\rho = 1$**	**$\rho = 0$**	**$\rho = -1$**
BA All Share Index	$ 1,000,000	10.0%	1	0.58%	3.77%	0.06	9.05	7.71	8.32	8.89
KSE General Index	$ (2,000,000)	−20.0%	1	0.71%	3.74%	0.14	5.6%	4.8%	5.2%	5.5%
MSM30 Index	$ 2,000,000	20.0%	1	0.79%	8.70%	0.10				
DSM20 Index	$ 3,000,000	30.0%	1	1.48%	8.07%	0.31	**Diversification benefits in EC**			
SE All Share Index	$ (4,000,000)	−40.0%	1	1.86%	11.03%	0.98	**$ (1.35)**	**−14.88%**		
Shuaa GCC Index	$ -	0.0%	1	1.30%	8.10%	1.05	**Annual economic capital (EC) in million AED [severe (crisis) market conditions]**			
Shuaa Arab Index	$ -	0.0%	1	1.15%	7.57%	1.00				
Total portfolio value in AED	$ 10,000,000	100%								
							ρ = Empirical	**$\rho = 1$**	**$\rho = 0$**	**$\rho = -1$**
Expected return and risk-adjusted return							57.08	52.56	52.55	52.55
Trading portfolio annual expected return		48.40%					35.4%	32.6%	32.6%	32.6%
Risk-adjusted expected return (normal)		53.47%					**Diversification benefits in EC**			
Risk-adjusted expected return (severe)		8.48%					**$ (4.53)**	**−7.93%**		
							Overall sensitivity factor: portfolio of stock indices			0.209

Source: Designed by the author using in-house built algorithms and software.

Table 12.5 Economic capital analysis under different market conditions, full case study

Asset allocation and economic capital analysis										
Stock market indices	Market value in AED	Asset allocation percentage	Liquidity holding horizon	Daily volatility (normal)	Daily volatility (severe)	Sensitivity factor	Annual economic capital (EC) in million AED [normal market conditions]			
DFM General Index	$ 6,000,000	60.0%	10	1.81%	12.16%	0.58				
ADSM Index	$ 4,000,000	40.0%	10	1.32%	7.08%	0.40				
							ρ = Empirical	$\rho = 1$	$\rho = 0$	$\rho = -1$
BA All Share Index	$ 1,000,000	10.0%	10	0.58%	3.77%	0.06	17.76	15.12	16.33	17.45
KSE General Index	$ (2,000,000)	−20.0%	10	0.71%	3.74%	0.14	11.0%	9.4%	10.1%	10.8%
MSM30 Index	$ 2,000,000	20.0%	10	0.79%	8.70%	0.10				
DSM20 Index	$ 3,000,000	30.0%	10	1.48%	8.07%	0.31	Diversification benefits in EC			
SE All Share Index	$ (4,000,000)	−40.0%	10	1.86%	11.03%	0.98	$ (2.64)	−14.88%		
Shuaa GCC Index	$ -	0.0%	10	1.30%	8.10%	1.05	Annual economic capital (EC) in million AED [severe (crisis) market conditions]			
Shuaa Arab Index	$ -	0.0%	10	1.15%	7.57%	1.00				
Total portfolio value in AED	$ 10,000,000	100%								
							ρ = Empirical	*$\rho = 1$*	*$\rho = 0$*	**$\rho = -1$**
Expected return and risk-adjusted return							112.01	103.13	103.12	103.11
Trading portfolio annual expected return		48.40%					63.9%	64.0%	63.9%	63.9%
Risk-adjusted expected return (normal)		27.25%					Diversification benefits in EC			
Risk-adjusted expectsed return (severe)		4.32%					$ (8.88)	−7.93%		
							Overall sensitivity factor: portfolio of stock indices			0.209

Source: Designed by the author using in-house built algorithms and software.

associations, the empirical correlation case considers the actual empirical correlation factors between all assets and is estimated via an $n \times n$ variance/covariance matrix. Therefore, with 97.5% confidence, the actual equity-trading portfolio should be expected to realize no greater than an AED9.05 million reduction in the value of annual economic capital over a one-day time frame. In other words, the loss of AED9.05 million in annual economic capital is one that an equity portfolio should realize only 2.5% of the time. If the actual loss exceeds the economic capital estimate, then this would be considered a violation of the assessment. From a risk management perspective, the economic capital estimation of AED9.05 million is a valuable piece of information. Since every equity-trading business has different characteristics, limited economic capital, and tolerances toward risk, the trading risk manager must examine the economic capital estimate relative to the overall position of the entire business. Simply put, can the firm tolerate or even survive such a rare event—a loss of AED9.05 million in its annual economic capital (or 5.6% of total portfolio value)? This question is not only important to the equity-trading unit, but also to financial institutions (or other funding units such as the treasury unit within the same hierarchy and organizational structure of the trading unit) who lend money to these trading units. The inability of a trading unit to absorb large losses may jeopardize its ability to make principal and interest payments. Therefore, various risk management strategies could be examined in the context of how they might affect the economic capital assessment. Presumably, risk management strategies, such as the use of futures and options contracts in hedging possible fluctuation in equity prices, should reduce the assessment of economic capital to set aside to absorb abnormal shocks. In other words, those extreme losses in equity trading, which would normally occur only 2.5% of the time, should be smaller with the incorporation of some types of risk management strategies.

Furthermore, the examination of economic capital under illiquid market conditions is performed with four different correlation factors: empirical correlations, zero, −100%, and +100% associations, respectively, and for long- and short-sale trading assets. Indeed, it is essential to include different correlation factors in any economic capital and stress-testing exercises. This is because existing trends in correlation factors may break down (or even change signs) under adverse market movements, caused by unforeseen financial or political events. In theory, the case with correlation +1 should provide the maximum economic capital statistics (i.e., AED7.71 million and AED15.12 million for both 1-day and 10-day closeout periods respectively) as a result of the fact that under these circumstances the total economic capital of actual trading portfolio is the weighted average of the individual economic capital of each equity-trading position. Furthermore, the degree of risk-diversification (namely, the effects of diversification benefits in economic capital) of this hypothetical portfolio can also be deduced simply as the difference in the statistics of the two greatest economic capitals—i.e., the economic capital of +100% correlation versus the empirical correlation case (i.e., AED−1.35 million or −14.88% for the case of normal market condition). However, it is appealing to note here that for this particular case, the economic capital under correlations +1 is less than the case with empirical correlations due to the impact of short selling of some assets. In addition, the overall systematic beta risk factor of this long/short-sale portfolio is indicated as 0.209, or in other words, the total equity portfolio value, with the actual asset allocation ratios, has little systematic risk. Moreover, expected returns and risk-adjusted expected returns (under both normal and severe market perspectives) are included in the risk analysis reports.

Finally, since the variations in economic capital are mainly related to the ways in which the multiple-asset are allocated in addition to their liquidation horizons, it is instructive to examine the way in which economic capital figures are influenced by changes in such parameters. All else equal, and under the assumption of normal and severe market outlooks, Table 12.5 demonstrates the non-linear alterations to economic capital figures when the closeout periods are increased in line, and across the board, to 10-day unwinding periods for all multiple-asset.

3.4 Nonlinear and dynamic optimization of efficient and coherent economic capital portfolios using L-VaR modeling algorithms

The portfolio mean-variance analysis approach, pioneered by Markowitz (1959), is one of the cornerstones of modern portfolio management and has served as the standard procedure for constructing efficient portfolios. Albeit Markowitz's mean-variance portfolio optimization methodology is a landmark in the development of modern investment theory, there are no risk measures universally adopted in financial applications. In the 1950s, Markowitz (1959) described the theoretical framework for modern portfolio theory and the creation of efficient portfolios under the notion of maximizing expected return subject to some risk constraints. In this framework, the risk is defined in terms of the standard deviation of each asset, which implies that the probability of negative returns, as the probability of positive returns, is weighted in the same way by the portfolio manager. As a result, the solution to the Markowitz theoretical models revolves around the portfolio weights, or the percentage of asset allocated in each security.

One of the basic problems of applied finance is the optimum selection of assets, with the aim of maximizing future returns and constraining risk by appropriate measures. To that end, Markowitz (1959) illustrated that, for a given level of risk, one can identify certain groups of equity securities that maximize expected return. He considered these optimum portfolios as "efficient" and referred to a continuum of such portfolios in dimensions of expected return and standard deviation as the efficient frontier. Accordingly, for asset allocation purposes, portfolio managers should choose portfolios located along the efficient frontier. Nevertheless, optimized portfolios do normally not perform as well in practice as one would expect from theory. For example, they are often outperformed by simple allocation strategies such as the equally weighted portfolio (Jobson and Korkie, 1981) or the global minimum variance portfolio (Jorion, 1991). Simply put, the "optimized" portfolio is not optimal at all. Portfolio weights are often not stable over time but change significantly each time the portfolio is re-optimized, leading to unnecessary turnover and increased transaction costs (Michaud, 1989; Fabozzi et al., 2006). Moreover, these portfolios typically present extreme holdings (i.e., "corner solutions") in a few securities while other securities have close to zero weight. It is well documented (Michaud, 1989) that mean-variance optimizers if left to their own devices, can sometimes lead to unintuitive portfolios with extreme positions in asset classes. Consequently, these "optimized" portfolios are not necessarily well diversified and exposed to unnecessary ex-post risk (Michaud, 1989). The reason for these phenomena is not a sign that mean-variance optimization does not work but rather that the modern portfolio theory framework is very sensitive to small changes in the inputs. In a portfolio optimization context, securities with large expected returns and low standard deviations will be overweighted and conversely, securities with low expected returns and high standard deviations will be underweighted. Therefore, large estimation errors in expected returns and/or variances/covariances will introduce errors in the optimized portfolio weights (Fabozzi et al., 2006).

As a result, for more than five decades a wide body of knowledge has been accumulated about the performance, strengths, and weaknesses of this approach when applied to equity portfolios. However, much less is known about portfolio optimization techniques in emerging equity markets, particularly under illiquid and adverse market circumstances. As such, in this chapter, we look at the optimization problem from a different realistic operational angle. In view of that, the optimization route is devised by finding the set of portfolios that minimize economic capital, with expected returns, trading volumes, and liquidation horizons constrained according to the requirements of the portfolio manager. As such, the focus in this work is on the forecast of risk measure, rather than on expected returns for two reasons: first, several studies have examined the forecasts of expected returns in the context of mean-variance optimization (see for instance, Best and Grauer, 1991). The common opinion is that expected returns are not easy to forecast and that the optimization process is very sensitive to these variations. Second, there exists a general notion that L-VaR and economic capital, in a wide sense, are simpler to assess than expected returns from historical data.

In this work, we implement a modeling algorithm for optimizing portfolio risk-return with economic capital constraints using realistic operational and financial scenarios and conduct different optimization case studies. These case studies show that the optimization algorithm, which is based on non-linear quadratic programming techniques, is very stable and efficient in managing different unwinding horizons and correlation factors. Moreover, the optimization algorithm can tackle a large number of equity assets as well as the integration of rational portfolio management operational scenarios. Indeed, the economic capital's risk management constraints, which are reduced to linear constraints, can be used in various applications to bound percentiles of the loss distributions.

3.5 Empirical constrained optimization of efficient and coherent economic capital portfolios—the case of long- and short-sale equity-trading assets

In this first research study, the optimization process is based on the definition of economic capital as the minimum possible loss over a specified time horizon within a given confidence level. The iterative-optimization modeling algorithm solves the problem by finding the market positions that minimize the loss, subject to that all constraints are satisfied within their boundary values. Further, in all optimization cases, the liquidation horizons as indicated in Tables 12.6–12.9 are assumed constant throughout the optimization process. For the sake of simplifying the optimization algorithm and thereafter its analysis, a hypothetical volume limit of 10 million AED is assumed as a constraint—i.e., the equity-trading entity must keep a maximum overall market value of different equities of no more than 10 million AED between long- and short-sale positions. As such, Figures 12.1 and 12.2 provide evidence of the empirical economic capital-efficient frontiers (under 1-day and 10-day closeout horizons respectively) defined using a 97.5% confidence level. As mentioned above, the optimum portfolio selection is performed by relaxing the short-sale constraint, for the different equity assets. On the other hand, efficient portfolios cannot always be attained (e.g. short sales without realistic lower boundaries on x_i) in the day-to-day real-world portfolio management operations and, hence, the portfolio manager should establish coherent portfolios under realistic and restricted dynamic budget constraints, detailed as follows:

- Total trading volume (between long- and short-sale equity-trading positions) is 10 million AED.
- Asset allocation for the long equity-trading position varies from 10% to 100%.
- Asset allocation for the short-sale equity-trading position varies from −10% to −60%.
- Liquidity horizons for all equities are kept constant throughout the optimization process according to the values indicated in Tables 12.6–12.9.

Now the weights are allowed to take negative or positive values. However, since arbitrarily high or low positive and negative weights have no financial investment sense, we determined to introduce lower and upper boundaries for the weights and in accordance with reasonable financial trading practices. Furthermore, for comparison purposes and since the endeavor in this work is to minimize economic capital, subject to specific expected returns, we decide to plot economic capital values versus expected returns, and not the opposite, as it is commonly the practice in the various portfolio management literature. Accordingly, the four benchmark portfolios (i.e., coherent portfolios [1,2,3,4]) lie off the efficient frontiers as shown in Figure 12.3. This is because the applied financial and operational constraints along with real-world investment considerations make it unlikely that a trading portfolio behaves exactly as the theory predicts. Imperfections such as restrictions on long- and short-sale positions, total volume, and liquidation horizons make it unlikely to generate an efficient equity portfolio. Thus, the portfolio manager should apply active strategies in order to earn excess returns. These

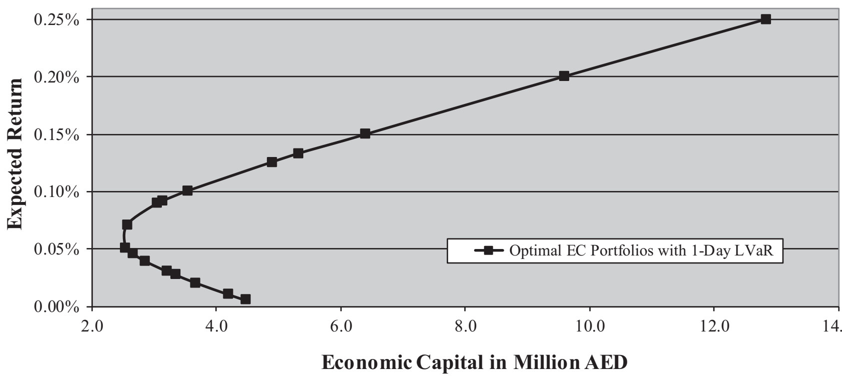

Figure 12.1 Optimal economic capital portfolios with 1-day L-VaR horizon (case of long and short trading positions).

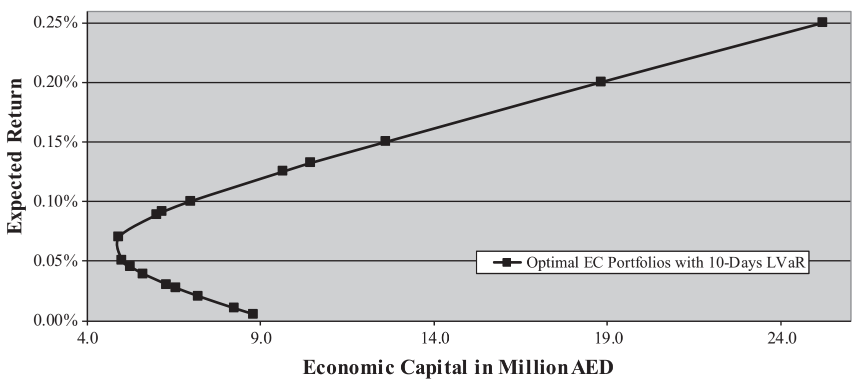

Figure 12.2 Optimal economic capital portfolios with a 10-day L-VaR horizon (case of long and short trading positions).

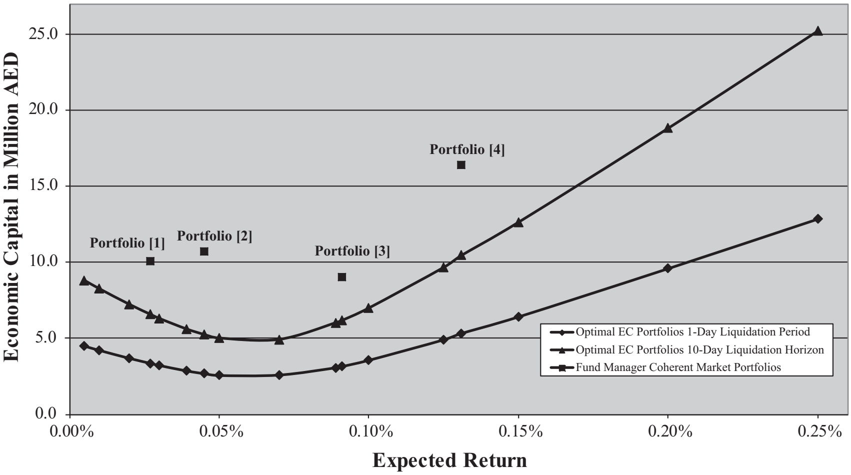

Figure 12.3 Optimal and coherent economic capital portfolios with different L-VaR horizons (case of long and short trading positions).

considerations are especially relevant for individual portfolio managers who may spread their trading positions across a few assets. Nevertheless, the elegance and compelling logic of the theory prompt attempts to apply the theory even though practitioners recognize the variance between the simplifying assumptions of the theory and the realities of the world.

In order to illustrate the composition of coherent portfolios [1,2,3,4], Tables 12.6–12.9 show the asset allocations in addition to their expected

Table 12.6 Fund manager economic capital coherent market portfolio [1] (case analysis of long and short trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ (3,000,000)	−30%
ADSM Index	3.0	$ 8,000,000	80%
BA All Share Index	4.0	$ 6,000,000	60%
KSE General Index	3.0	$ (2,000,000)	−20%
MSM30 Index	5.0	$ 6,000,000	60%
DSM20 Index	6.0	$ (1,000,000)	−10%
SE All Share Index	3.0	$ (4,000,000)	−40%
ρ	*EC (Normal)*	*EC/Volume*	*Annual Expected Return*
Empirical	10,076,454	6.2%	9.72%
1.0	2,200,724	1.4%	**Sensitivity Factor**
0.0	12,340,256	7.7%	−0.215

Source: Designed by the author using in-house built algorithms and software.

Table 12.7 Fund manager economic capital coherent market portfolio [2] (case analysis of long and short trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ (2,000,000)	−20%
ADSM Index	3.0	$ 2,000,000	20%
BA All Share Index	4.0	$ 6,000,000	60%
KSE General Index	3.0	$ 3,000,000	30%
MSM30 Index	5.0	$ (2,000,000)	−20%
DSM20 Index	6.0	$ (3,000,000)	−30%
SE All Share Index	3.0	$ 6,000,000	60%
ρ	**EC (Normal)**	**EC/Volume**	**Annual Expected Return**
Empirical	10,740,249	6.7%	16.20%
1.0	6,961,365	4.3%	**Sensitivity Factor**
0.0	11,061,832	6.9%	0.469

Source: Designed by the author using in-house built algorithms and software.

Table 12.8 Fund manager economic capital coherent market portfolio [3] (case analysis of long and short trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ 3,000,000	30%
ADSM Index	3.0	$ 2,000,000	20%
BA All Share Index	4.0	$ 3,000,000	30%
KSE General Index	3.0	$ (2,000,000)	−20%
MSM30 Index	5.0	$ 1,000,000	10%
DSM20 Index	6.0	$ (1,000,000)	−10%
SE All Share Index	3.0	$ 4,000,000	40%
ρ	**EC (normal)**	**EC/volume**	**Annual expected return**
Empirical	9,050,784	5.6%	32.76%
1.0	11,921,747	7.4%	**Sensitivity factor**
0.0	8,034,212	5.0%	0.513

Source: Designed by the author using in-house built algorithms and software.

returns and systematic risk factors. Similarly, the four tables depict the minimum economic capital required to sustain the operations of these portfolios and the ratio of Economic Capital /Volume with the use of three different correlation parameters. In this way, portfolio managers should employ risk measures, which allow them to take decisions that would produce a risk budget lower than a specific target. Thus, this portfolio analysis is substantially a key improvement to the conventional Markowitz (1959) technique as our modeling algorithms and optimization techniques permit the determination of the asymmetric aspect of risk under different market outlooks. In any case, the benefit of portfolio optimization critically depends on how accurately the implemented economic capital risk measure is forecasted.

Table 12.9 Fund manager economic capital coherent market portfolio (AlJanabi, 2021) (case analysis of long and short trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ 10,000,000	100%
ADSM Index	3.0	$ (6,000,000)	−60%
BA All Share Index	4.0	$ 6,000,000	60%
KSE General Index	3.0	$ (2,000,000)	−20%
MSM30 Index	5.0	$ (6,000,000)	−60%
DSM20 Index	6.0	$ 3,000,000	30%
SE All Share Index	3.0	$ 5,000,000	50%
ρ	**EC (normal)**	**EC/volume**	**Annual expected return**
Empirical	16,375,682	10.2%	47.52%
1.0	17,736,375	11.0%	**Sensitivity factor**
0.0	18,746,835	11.6%	0.746

Source: Designed by the author using in-house built algorithms and software.

3.6 Empirical optimization of efficient and coherent economic capital portfolios—the case of long-only equity-trading assets

For the sake of comparison of the first empirical optimization procedure with other real-world operational constraints, a second optimization process is carried out, however, this time by considering long-only trading positions and by imposing a restriction on short sales of equities.

Similarly, in this second case study, the optimization algorithm is based on the definition of economic capital as the minimum possible loss over a specified time horizon, and within a given confidence level. The optimization algorithm solves the problem by finding the market long-only equity positions that minimize the loss, subject that all financial and operational constraints are satisfied within their boundary values. Further, in all optimization cases, the liquidation horizons as indicated in Tables 12.10–12.13 are assumed constant throughout the optimization process. Likewise, for the sake of simplifying the optimization routine and thereafter its analysis, a hypothetical volume limit of AED10 million is assumed as a constraint—i.e., the equity-trading entity must keep a maximum overall market value of different equities of no more than AED10 million of long-only trading assets. As such, Figures 12.4 and 12.5 provide evidence of the empirical economic capital efficient frontiers (under *1*-day and *10*-day liquidation horizons respectively) defined using a 97.5% confidence level. As indicated above, the optimum portfolio selection is performed by imposing a short-sale prohibition constraint, for the different equity assets. As a result, efficient portfolios cannot always be attained in the day-to-day real-world portfolio management operations and, hence, the portfolio manager should establish coherent portfolios under realistic and restricted dynamic budget constraints, detailed as follows:

- Total trading volume of long-only equity-trading positions is AED10 million.
- Asset allocation for the long-only equity-trading position varies from 0% to 60%.
- Liquidity horizons for all equities are kept constant throughout the optimization process according to the values indicated in Tables 12.10–12.13.

In this particular optimization case study, the weights are allowed to take only positive values. However, since arbitrarily high or low positive weights could have no financial investment sense, we determined to introduce lower and upper boundaries for the weights and in accordance with reasonable financial trading practices. As a result, the four benchmark portfolios (i.e., economic capital coherent portfolios [1], [2], [3], and [4]) are located more closely to the efficient frontiers than in the earlier optimization case, as shown in Figure 12.6. As discussed above, it seems that this optimization phenomenon could not be attained for long- and short-sale trading positions because financial and operational real-world portfolio management considerations make it unlikely that a trading portfolio behaves exactly as the theory predicts. However, for long-only trading positions, it seems that it is possible to get closer to the efficient frontier and synchronize to a certain degree the performance of both efficient and coherent economic capital portfolios.

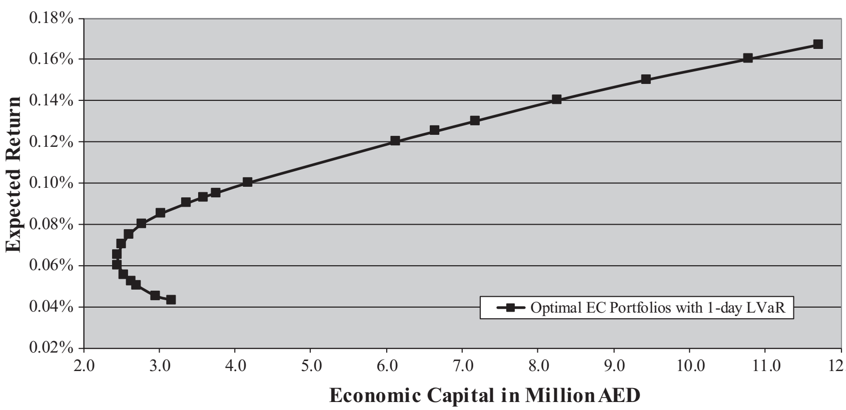

Figure 12.4 Optimal economic capital portfolios with 1-day L-VaR horizon (case of long trading positions).

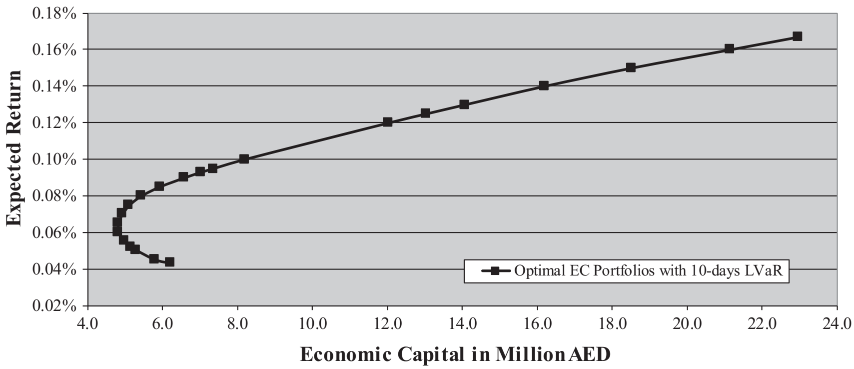

Figure 12.5 Optimal economic capital portfolios with 10-day L-VaR horizon (case of long trading positions).

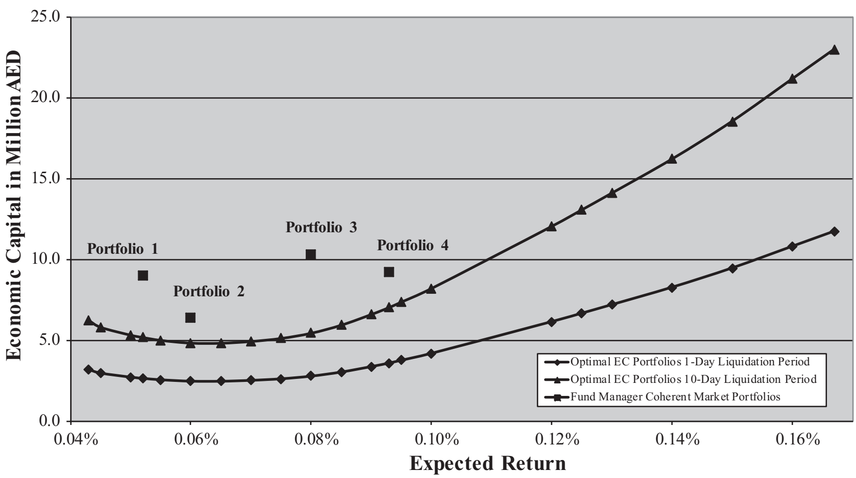

Figure 12.6 Optimal and coherent economic capital portfolios with different L-VaR horizons (case of long trading positions).

Finally, in order to illustrate the composition of economic capital coherent portfolios [1], [2], [3], and [4], Tables 12.10–12.13 show the asset allocations in addition to their expected returns and systematic risk factors. Similarly, the four tables depict the minimum economic capital required to sustain the operations of these portfolios and the ratio of economic capital/volume with the use of three different correlation parameters.

Table 12.10 Fund manager economic capital coherent market portfolio (AlJanabi, 2020) (case analysis of long trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ -	0%
ADSM Index	3.0	$ -	0%
BA All Share Index	4.0	$ 1,000,000	10%
KSE General Index	3.0	$ -	0%
MSM30 Index	5.0	$ 3,000,000	30%
DSM20 Index	6.0	$ 6,000,000	60%
SE All Share Index	3.0	$ -	0%
ρ	**EC (normal)**	**EC/volume**	**Annual expected return**
Empirical	9,017,268	5.6%	18.72%
1.0	10,891,404	6.8%	**Sensitivity factor**
0.0	8,753,038	5.4%	0.149

Source: Designed by the author using in-house built algorithms and software.

Table 12.11 Fund manager economic capital coherent market portfolio (AlJanabi, 2020) (case analysis of long trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ 2,000,000	20%
ADSM Index	3.0	$ 2,000,000	20%
BA All Share Index	4.0	$ 1,000,000	10%
KSE General Index	3.0	$ 1,000,000	10%
MSM30 Index	5.0	$ 1,000,000	10%
DSM20 Index	6.0	$ 1,000,000	10%
SE All Share Index	3.0	$ 2,000,000	20%
ρ	**EC (normal)**	**EC/volume**	**Annual expected return**
Empirical	6,397,150	4.0%	30.60%
1.0	11,090,813	6.9%	**Sensitivity factor**
0.0	4,984,717	3.1%	0.369

Source: Designed by the author using in-house built algorithms and software.

4 Conclusion

Recent years have witnessed the increasing role of investment funds in equity markets and with a particular emphasis on emerging markets. Emerging equity assets, in addition to offering high-expected rates of return, also offer significant risk management benefits since these assets are customarily characterized by lower correlations between each other and with other

Table 12.12 Fund manager economic capital coherent market portfolio (AlJanabi, 2020) (case analysis of long trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ 5,000,000	50%
ADSM Index	3.0	$ 2,000,000	20%
BA All Share Index	4.0	$ -	0%
KSE General Index	3.0	$ -	0%
MSM30 Index	5.0	$ -	0%
DSM20 Index	6.0	$ -	0%
SE All Share Index	3.0	$ 3,000,000	30%
ρ	**EC (normal)**	**EC/volume**	**Annual expected return**
Empirical	10,304,955	6.4%	42.48%
1.0	13,898,201	8.6%	**Sensitivity Factor**
0.0	8,825,850	5.5%	0.550

Source: Designed by the author using in-house built algorithms and software.

Table 12.13 Fund manager economic capital coherent market portfolio (AlJanabi, 2021) (case analysis of long trading positions)

Market index	*Liquidation period (in days)*	*Market value in AED*	*Asset allocation per market*
DFM General Index	3.0	$ 6,000,000	60%
ADSM Index	3.0	$ -	0%
BA All Share Index	4.0	$ -	0%
KSE General Index	3.0	$ 3,000,000	30%
MSM30 Index	5.0	$ 1,000,000	10%
DSM20 Index	6.0	$ -	0%
SE All Share Index	3.0	$ -	0%
ρ	**EC (normal)**	**EC/volume**	**Annual expected return**
Empirical	9,238,413	5.7%	48.24%
1.0	11,082,185	6.9%	**Sensitivity Factor**
0.0	8,960,523	5.6%	0.319

Source: Designed by the author using in-house built algorithms and software.

financial assets. As such, investment funds, traditionally dealing with developed financial markets, are now diversifying into emerging equity markets with the objective of achieving significant risk-return tradeoffs. The focus on emerging equity markets is motivated by the fact that many of these markets have progressively moved toward market-based systems, liberalized stocks, bonds, foreign exchange, derivatives markets, and relaxed restrictions on foreign investor participation.

The last few years have witnessed a rapid expansion of emerging markets equity-trading activities—with several turmoil in capital markets—and an increasing interest in the measurement and management of liquidity risk for portfolio management and asset allocation purposes. During the last decade, L-VaR and coherent economic capital allocation became two of the most popular tools for assessing trading risk across financial institutions. It is thus essential, at this stage, to be able to adapt the definition of traditional tools of quantifying trading risk to the needs and the requirements of this new environment in which the liquidity factor plays a central role. Indeed, asset liquidity is a key factor in measuring the overall trading risk, and neglecting liquidity risk can lead to an underestimation of the total risk and undercapitalization of financial institutions, particularly if their portfolios are concentrated in emerging markets. This has assumed special significance as more and more financial entities, particularly in emerging markets, prepare themselves toward better internal modeling of trading risk, within the context of Basel II and Basel III capital adequacy guidelines.

In this chapter, we examine how to determine coherent economic capital portfolio choice for an equity portfolio manager under the assumption of different liquidation horizons and by implementing different long-only trading scenarios or a combination of long- and short-sale trading strategies. We then implement a robust portfolio optimization algorithm using L-VaR as a risk measure subject to the application of meaningful financial and operational constraints. In the final section of this chapter, we describe the selection process for coherent economic capital portfolios, of either long-only assets or a combination of long- and short-sale positions, and provide the composition of each coherent portfolio. In addition to the standard economic capital optimization algorithm that is adjusted for liquidity risk, related topics such as multi-horizon portfolio selection models and robust L-VaR and economic capital optimization techniques with various dependence measures are discussed. To that end, in this research study, the implemented modeling techniques and the non-linear robust optimization algorithms are based on the Al Janabi model (Al Janabi, 2008; Madoroba and Kruger, 2014) and can have important uses and applications in machine learning and artificial intelligence, machine learning for the policymaking process, the IoT, and machine learning techniques for IoT data analytics.

Given the rising need for measuring, managing, and controlling the financial risk, trading risk prediction under liquid and illiquid market conditions plays an increasing role in the banking and finance sectors. Moreover, the ability to focus on other moments in the return distribution with the possibility of allowing for skewed or leptokurtotic distributions enables additional risk factors (along with the use of conditional volatility) to be included in the coherent economic capital portfolio selection problem. To that end, in this chapter, we implement a robust internal model of liquidity trading risk management for multiple-asset portfolios. This is with the objective of predicting economic capital under illiquid market outlooks and within a multivariate context. Using more than 6 years of daily return data of emerging GCC markets, we examine various trading portfolios and determine the risk exposure under different illiquid market conditions and correlation parameters. Indeed, the selected data falls within the most extreme events of the 2007–2008 global financial meltdown.

The empirical testing is provided using nine equity indices for the GCC zone. Several case studies for the computation of L-VaR and economic capital are performed to demonstrate how the new optimization techniques can be implemented in real-world stock markets. The empirical findings indicate that the implemented novel modeling techniques and optimization algorithms perform adequately over the entire sampling period and across alternative investment horizons. The empirical results indicate that L-VaR and economic capital depend on the minimum expected return and conditional volatility as measured by the GARCH-M (1,1) model, degree of correlation factors under adverse market setting, individual L-VaR positions, liquidity horizons of each asset, and the set of portfolio weights.

To investigate the statistical properties of the data, we have computed the log returns of each series. However, it is a stylized fact that the distributions of the returns of many financial time series are non-normal, with skewness and kurtosis pervasive. As such, it would therefore be more desirable to focus on a measure for risk that is able to incorporate any non-normality in the return distributions of financial assets. For almost all the cases, the study of some preliminary statistics allows us to conclude that the considered data are characterized by asymmetry and high leptokurtosis. Moreover, the normality hypothesis has been rejected for almost every time series through the JB test. As a result, the use of the normal distribution, which is the case in the mean-variance (Markowitz, 1959) approach, tends to give poor evidence of what is observed in our returns time series. In fact, the computation of L-VaR under the normality assumption can underestimate the actual risk exposures since the tails of the empirical distribution are fatter than those implied by the normal one. To overcome this shortcoming, in this work, we implement the empirical distribution of past returns for all equity assets. This modeling technique provides a better examination of L-VaR and a proper assessment of economic capital, especially under severe and illiquid market outlooks. The empirical results we report in this chapter suggest that the introduction of L-VaR and economic capital into an asset allocation model allows the portfolio manager to focus attention on the downside risk. In particular, the developed optimization algorithm allows the trading assets that must enter the coherent portfolio in order to meet a shortfall constraint (defined as the L-VaR or economic capital limit) to be determined.

The implemented modeling algorithms and obtained empirical results are interesting in terms of theory as well as practical applications and can have many uses and application in financial markets, especially in the wake of the

2007–2009 global financial crunch. In addition, the implemented optimization techniques and risk assessment algorithms can aid in advancing quantitative risk management practices in emerging and developed markets, particularly in light of the 2007–2009 financial turmoil. Similarly, it can aid in the progress of RegTech for the global financial services industry and can be of interest to professionals, regulators, and researchers working in the field of financial engineering, FinTech, machine learning for the policymaking process, and machine learning techniques for the IoT data analytics; and for those who want to advance their understanding of the impact of innovative risk computational techniques and reporting processes on regulatory challenges for the financial services industry and its effects on global financial stability. Furthermore, it provides key practical implications for portfolio and risk managers, treasury directors, risk management executives, policymakers and financial regulators to comply with the requirements of Basel III best practices on liquidly risk and capital adequacy.

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Notes

1 For further details on the modeling techniques and optimization algorithms, we refer the readers to the associated chapter published in this book, entitled: Optimization Algorithms for Multiple-Asset Portfolios with Machine Learning Techniques: Theoretical Foundations of Optimum and Coherent Economic Capital Structures, authored by: Mazin A. M. Al Janabi.

2 In this chapter, the concept of coherent market portfolios refers to rational portfolios that are contingent on meaningful financial and operational constraints. In this sense, coherent market portfolios do not lie on the efficient frontiers as defined by Markowitz (1959) and instead have logical and well-structured long-only and combinations of long and short-sales asset allocations.

3 Economic capital (or risk capital) can be defined as the minimum amount of equity capital a financial entity needs to set aside to absorb worst losses over a certain time horizon with a certain confidence level. This is with the objectives of sustaining its trading operations activities and without subjecting itself to insolvency matters. Economic capital can be assessed with an internal method and modeling techniques such as L-VaR. Economic capital differs somehow from regulatory capital, which is necessary to comply with the requirements of Basel II and Basel III capital adequacy accords. However, building internal market risk modeling techniques to assess economic capital can significantly aid the financial entity in complying with Basel II and Basel III capital adequacy requirements.

4 In this chapter, robust risk management modeling techniques are used to compute the potential loss exposure due to an event risk that is associated with large

movements of the GCC stock markets indices, under the assumption that certain GCC financial markets have typical 3–12% leap during periods of financial turmoil (Al Janabi, 2008, 2012, 2013, 2014). The task here is to measure the potential trading risk exposure that is associated with a pre-defined leap and under the notion of several correlation factors and liquidation horizons.

5 For other relevant literature on liquidity risk, asset pricing, internal risk models, machine learning, and portfolio choice and diversification one can refer as well to Al Janabi (2019, 2021a,b,c), Kalayci et al. (2019), Ban et al. (2018), Paiva et al. (2019), Asadi and Al Janabi (2020), Arreola-Hernandez and Al Janabi (2020), Ruozi and Ferrari (2013), Grillini et al. (2019), Roch and Soner (2013), Weiß and Supper (2013), Al Janabi et al. (2019), Amihud et al. (2005), Takahashi and Alexander (2002), Arreola-Hernández et al. (2015, 2017), Cochrane (2005), and Meucci (2009), among others.

6 The issue of improving the precision of L-VaR estimates, under the effects of non-normality and at extreme quantiles, can be tackled by using the Cornish–Fisher expansion (Cornish and Fisher, 1937). In fact, the Cornish–Fisher expansion is a semi-parametric technique that estimates quantiles of non-normal distributions as a function of standard normal quantiles and the sample skewness and excess kurtosis and can account properly for the strong negative skewness in equity returns at the time of a crash or event (crisis) market conditions (Alexander, 2008). In the context of parametric L-VaR, this technique allows extreme quantiles to be estimated from standard normal quantiles at high significance levels, given only the first four moments of the empirical return distribution. As such, distributions that are approximated using Cornish–Fisher expansion may offer significant improvement on backtesting results for a standard parametric L-VaR model. Therefore, Cornish–Fisher approximation is quick and easy to use, however it is only accurate if the portfolio returns are not too highly skewed or leptokurtic. In such a case, Johnson's SU distribution and algorithm can provide better approximations to the parametric L-VaR at extreme quantiles than the Cornish–Fisher L-VaR.

7 In this chapter, severe or crisis market conditions refer to unexpected extreme adverse market situations at which losses could be several-fold larger than losses under normal market situation. Stress-testing technique is usually used to estimate the impact of unusual and severe events.

13 An Overview of Neural Network in Financial Risk Management

Maha Metawea, Saad Metawa and Noura Metawa

1 Background

The artificial neural network (ANN) has been widely rising over the last few years; in 1953, Warren S. McCulloch, a neuroscientist, and Walter Pitts, a logician, developed the first conceptual model of an ANN. In their paper, "A logical calculus of the ideas imminent in nervous activity," they describe the concept of a neuron, a single cell living in a network of cells that receives inputs, processes those inputs, and generates an output.

Their work, and the work of many scientists and researchers that followed, was not meant to accurately describe how the biological brain works. Rather, an ANN (which we will now simply refer to as a "neural network") was designed as a computational model based on the brain to solve certain kinds of problems. Many researchers tried to define it in the following terms.

2 Neural Networks: Concepts and Definitions

According to DARPA (1988): "A neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes."

According to Haykin (1995): "A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process.
2. Interneuron connection strengths known as synaptic weights are used to store the knowledge."

According to Nigrin (1993): "A neural network is a circuit composed of a very large number of simple processing elements that are neutrally based. Each element operates only on local information. Furthermore, each element operates asynchronously; thus there is no overall system clock."

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According to Zurada (1992): "Artificial neural systems, or neural networks, are physical cellular systems which can acquire, store, and utilize experiential knowledge."

According to Investopedia: A neural network (NN) is a series of algorithms that attempts to identify underlying relationships in a set of data by using a process that mimics the way the human brain operates. NNs have the ability to adapt to changing input so the network produces the best possible result without the need to redesign the output criteria. The concept of NNs is rapidly increasing in popularity in the area of developing trading systems.

In finance, NNs are used for time-series forecasting, algorithmic trading, securities classification, credit risk modeling, and constructing proprietary indicators and return derivatives.

According to Wikipedia: An NN is a computational approach, which is based on a large collection of neural units (AKA artificial neurons), loosely modeling the way a biological brain solves problems with large clusters of biological neurons connected by axons. Each neural unit is connected with many others, and links can be enforcing or inhibitory in their effect on the activation state of connected neural units. Each individual neural unit may have a summation function that combines the values of all its inputs together. There may be a threshold function or limiting function on each connection and on the unit itself: such that the signal must surpass the limit before propagating to other neurons. These systems are self-learning and trained, rather than explicitly programmed, and excel in areas where the solution or feature detection is difficult to express in a traditional computer program.

3 Characteristics and Advantages of NNs

In the following listed studies, we shed the light on the most important papers that dealt with neural in several patterns.

Boritz and Kennedy (1995) conducted a comprehensive study on the effectiveness of NN types in the prediction of business failure. This study was discussing the effectiveness of forecasting the bankruptcy filing using different neural types. In this study, two patterns have been used to predict business failure (back-propagation and optimal estimation theory), in the back-propagation method, they use four different models (cumulative predictive back-propagation, back-propagation, pruned back-propagation, and functional link back-propagation).

The sample of bankrupt companies used for the present study was obtained from Boritz et al. (1995) which was based on the data set developed by Kennedy and Shaw (1991). The sample consisted of 171 companies that filed for bankruptcy between 1971 and 1985 inclusive. Kennedy and Shaw (1991) determined the exact date of bankruptcy filing for all companies in the data set. For both the bankrupt and non-bankrupt firms, data were collected to allow the calculation of the variables.

Naeini et al. (2010) have listed some special characteristics of NNs:

First, the traditional methods such as linear regression and logistic regression are <u>models based</u> while <u>NN</u>s are <u>self-adjusting methods based</u> on training data, so they have the ability to solve the problem with a little information about its model and without constraining the prediction model by adding any extra assumptions. NNs are well applied to the problems in which extracting the relationships among data is really difficult.

Second, NNs have generalization ability as they can recognize a new situation even if they haven't been in the training set, as recognition problems predicting future events (unseen data) are based on previous data (training set), the application of NNs would be very beneficial.

Third, NNs proved that they can approximate any complex continuous function that enables us to explain any complicated relationship between the input and the output of the system.

According to Yadav et al. (2013), NN has the ability to deal with important information from different sets of data, which is suitable when using financial time series.

As we mentioned before, the NN can be a very useful tool for time-series modeling and forecasting. Much research has been conducted on the applications of NNs for solving different financial issues as a result, NNs are mostly implemented in forecasting stock returns, takings, and stock modeling.

Malliaris and Salchenberger (1996) have defined NNs as an information processing technology that models mathematical relationships between inputs and outputs. Based on the architecture of the human brain, a set of processing elements or neurons (nodes) are interconnected and organized in layers. These layers of nodes can be structured hierarchically, consisting of an input layer, an output layer, and middle (hidden) layers.

Also, **Shachmurove** (2011) has defined NNs as "non-linear models that can be trained to map past and future values of time-series data and thereby extract hidden structures and relationships that govern the data."

He proposed that NN is better than traditional ways of analysis as NNs make no assumptions about the nature of the distribution of the data and so that, the analysis will be fair without any biased results. Also, time-series data are dynamic in nature, it is necessary to have non-linear tools in order to discuss relationships among time-series data. Finally, he stated that NNs do well with missing or incomplete data.

On the other hand, he listed the disadvantages of NNs that may vary according to the situation or type of data,

First, no estimation or prediction errors are calculated with an artificial NN (ANN) (Caporaletti et al., 1995).

Second, ANNs are "black boxes," for it is impossible to figure out how relations in hidden layers are estimated (Li, 1995).

Third, the network may hardly fit a curve to some data especially when there is no relationship.

Finally, NNs have long training times. Reducing training time is vital because building and forming a NN forecasting system is a process of trial and error.

Hamid (2009) also defines NNs as

> a computational technique that benefits from techniques similar to ones employed in the human brain. It is designed to mimic the ability of the human brain to process data and information and comprehend patterns. It imitates the structure and operations of the three dimensional lattice of network among brain cells (nodes or neurons, and hence the term neural.

The input layer uses the data and acts as an independent variable; therefore, the amount of neurons in the input layer depends on the variable. The output layer acts as a dependent variable and the amount of neurons in this layer depends on the dependent variables.

Monfared and Enke (2015) have also discussed the different aspects of hybrid NN; they reveal that NN is more useful in an extremely volatile environment, but in stable situations, it's not beneficial to use hybrid NN because of the lack of complexity in data.

NNs consist of nodes and weights for to what extent of effect which one node has on other nodes.

The nodes are coordinated in a pattern with a sequence of input nodes forming the base layer, one or more output nodes at the top layer, and one or more hidden layers of nodes between the input and output layers.

NN architectures have two phases, feedback or feed forward.

<u>In a feed-forward network phase</u>, inputs are only received from previous layers. So that the information always streams in a forward direction, from the input nodes, crossing hidden layers of nodes, and finally output nodes.

The back-propagation pattern, a common training method for NNs, is a feed-forward network.

The other phase of NNs is a feedback network; in this phase, nodes can receive inputs from any other player in the network (either in the same layer); the direction of information flow is not bounded.

The process of NNs has two stages, learning and testing. In the learning stage, the network is used to solve certain problems or identify specific matter based on given information. Two types of learning are available for network operation, supervised and unsupervised learning.

In the supervised learning mode, the network is approached with a set of facts along with the correct response. The network uses the information and correct response to formulate connection weights for each node in the network.

In unsupervised learning, the network is approached with a set of facts, but the network has an unknown response. The network processes the input data and formulates an algorithm to classify the presented input. This type of learning can be viewed as a multivariate mechanism to explore the underlying framework of the data.

ANNs: they are a type of statistical learning algorithm that resembles biological NNs. They are used to estimate functions that can depend on a large number of inputs and are generally unknown.

ANNs have some key advantages that make them most suitable for certain problems and situations:

1 ANNs have the ability to learn and model non-linear and complex relationships, which is really important because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex.
2 ANNs can generalize—After learning from the initial inputs and their relationships, it can infer unseen relationships on unseen data as well, thus making the model generalize and predict on unseen data.
3 Unlike many other prediction techniques, ANN does not impose any restrictions on the input variables (like how they should be distributed). Additionally, many studies have shown that ANNs can better model heteroscedasticity, i.e. data with high volatility and non-constant variance, given its ability to learn hidden relationships in the data without imposing any fixed relationships in the data. This is something very useful in financial time-series forecasting (e.g. stock returns) where data volatility is very high.

4 Basic Features and Types of ANN

ANNs are the biologically inspired simulations performed on the computer to perform certain specific tasks like clustering, classification, pattern recognition, etc.

An ANN, in general, is a biologically inspired network of artificial neurons configured to perform specific tasks.

NNs resemble the human brain in the following two ways:

- An NN acquires knowledge through learning.
- An NN's knowledge is stored within inter-neuron connection strengths known as synaptic weights (Figure 13.1).

The dendrites in a biological NN are analogous to the weighted inputs based on their synaptic interconnection in an ANN.

The cell body is analogous to the artificial neuron unit in the ANN which also comprises summation and threshold units.

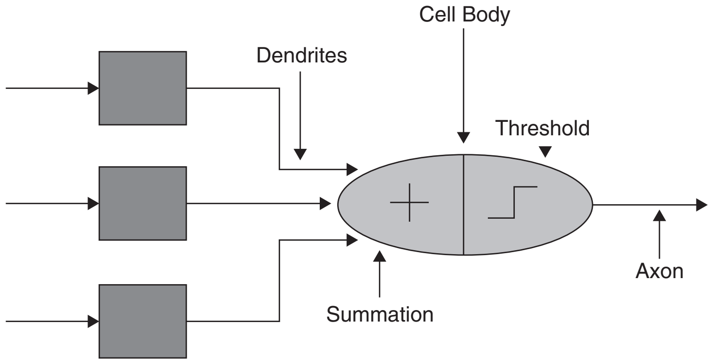

Figure 13.1 Analogy of ANN with a biological NN.

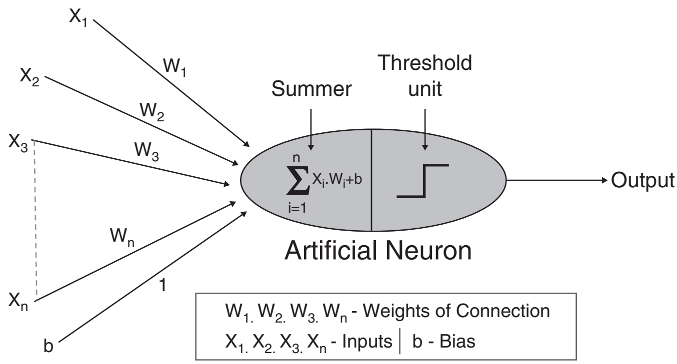

Figure 13.2 How does ANN work?

Axon carries output that is analogous to the output unit in the case of an ANN. So, ANNs are modeled using the working of basic biological neurons (Figure 13.2).

ANNs can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges with weights are connections between neuron outputs and neuron inputs.

The ANN receives input from the external world in the form of a pattern and image in the vector form. These inputs are mathematically designated by the notation $x(n)$ for n number of inputs.

Each input is multiplied by its corresponding weights. Weights are the information used by the NN to solve a problem. Typically weight represents the strength of the interconnection between neurons inside the NN.

The weighted inputs are all summed up inside the computing unit (artificial neuron). In case the weighted sum is zero, bias is added to make the output not- zero or to scale up the system response. Bias has the weight and input always equal to "1".

The sum corresponds to any numerical value ranging from 0 to infinity. In order to limit the response to arrive at the desired value, the threshold value is set up. For this, the sum is passed through the activation function.

The activation function is a set of the transfer function used to get the desired output. There are linear as well as the non-linear activation function.

Some of the commonly used activation functions are—binary, sigmoid (linear), and tan hyperbolic sigmoid functions (nonlinear).

- **Binary**—The output has only two values either 0 or 1. For this, the threshold value is set up. If the net weighted input is greater than 1, an output is assumed 1 otherwise zero.
- **Sigmoid Hyperbolic**This function has an "S" shaped curve. Here, the tan hyperbolic function is used to approximate output from net input. The function is defined as—$f(x) = (1/1 + \exp(-\sigma x))$ where σ—steepness parameter.

A typical NN contains a large number of artificial neurons called units arranged in a series of layers (Figure 13.3).

- **Input layer**—It contains those units (artificial neurons) which receive input from the outside world on which the network will learn, recognize, or otherwise process.
- **Output layer**—It contains units that respond to the information about how it's learned any task.
- **Hidden layer** —These units are in between input and output layers. The job of the hidden layer is to transform the input into something that the output unit can use in some way.

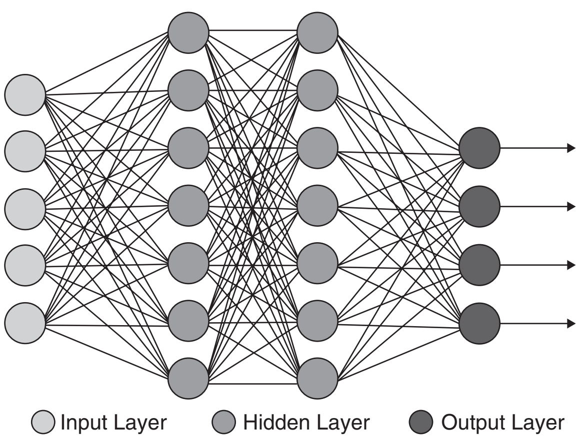

Figure 13.3 Different layers in a typical ANN.

Most NNs are fully connected that means to say each hidden neuron is fully connected to every neuron in its previous layer(input) and to the next layer (output) layer (Figure 13.4).

Other types of the NN:

- **Modular NN**: It is the combined structure of different types of the NN like multilayer perception (MLP), Hopfield network, recurrent NN, etc., which are incorporated as a single module into the network to perform independent subtask of whole complete NNs.
- **Physical NN**: In this type of ANN, electrically adjustable resistance material is used to emulate the function of synapse instead of software simulations performed in the NN.

5 Learning in ANNs

The NN learns by adjusting its weights and bias (threshold) iteratively to yield the desired output. These are also called free parameters. For learning to take place, the NN is trained first. The training is performed using a defined set of rules also known as the learning algorithm.

5.1 Popular Learning Algorithms Used in NN

- **Gradient Descent**—This is the simplest training algorithm used in the case of a supervised training model. In case, the actual output is different from the target output, the difference or error is find out. The gradient descent algorithm changes the weights of the network in such a manner to minimize this error.
- **Back-propagation**—It is an extension of the gradient-based delta learning rule. Here, after finding an error (the difference between desired and target), the error is propagated backward from the output layer to the input layer via a hidden layer. It is used in the case of multilayer NNs.

5.2 Types of Learning in NN

- **Supervised learning**: In the supervised learning stage, the training data are inputs to the network, and the desired output is the known weights, and they are adjusted until the output yields desired value.
- **Unsupervised learning**: The input data are used to train the network whose output is known. The network classifies the input data and adjusts the weight by feature extraction in input data.
- **Reinforcement learning**: Here, the value of the output is unknown, but the network provides feedback on whether the output is right or wrong. It is semi-supervised learning.

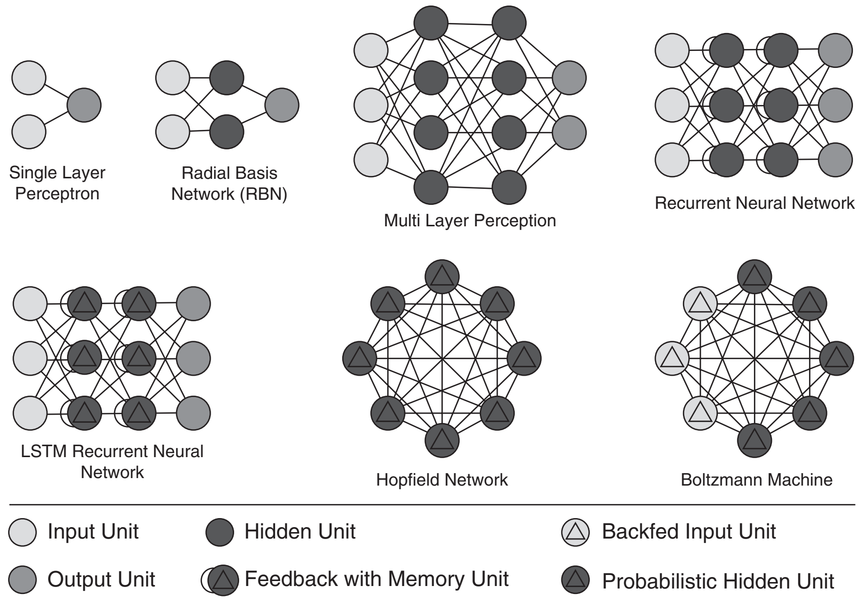

Figure 13.4 Popular NN architectures.

- **Offline learning**:The adjustment of the weight vector and threshold is done only after all the training set is presented to the network. It is also called batch learning.
- **Online learning**: The adjustment of the weight and threshold is done after presenting each training sample to the network.
- **Training set:** A set of examples used for learning that is to fit the parameters [i.e. weights] of the network. One Epoch comprises one full training cycle on the training set.
- **Validation set**: A set of examples used to tune the parameters [i.e. architecture] of the network.

For example, to choose the number of hidden units in an NN.

- **Test set:** A set of examples used only to assess the performance [generalization] of a fully specified network or to apply successfully in predicting output whose input is known.

The second pattern is input to the network. This time, weights are not initialized to zero. The initial weights used here are the final weights obtained after presenting the first pattern. By doing so, the network is able to continue weight adjustments.

So, these weights correspond to the learning ability of the network to classify the input patterns successfully.

Four different uses of NNs:

- **Classification**—An NN can be trained to classify a given pattern or data set into a predefined class. It uses feed forward networks.
- **Prediction**—An NN can be trained to produce outputs that are expected from a given input.
- **Clustering**—The NN can be used to identify a special feature of the data and classify them into different categories without any prior knowledge of the data.

The following networks are used for clustering:

- Competitive networks
- Adaptive Resonance Theory Networks
- Kohonen Self-Organizing Maps.
- **Association**—An NN can be trained to remember a certain pattern, so that when the noise pattern is presented to the network, the network associates it with the closest one in the memory or discard it. Hopfield Networks which performs recognition, classification, clustering, etc. (Figure 13.5).

Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest from their background, and make sound and reasonable decisions about the categories of the patterns.

So, the recognition problem here is essentially a classification or categorized task.

Approaches used for pattern recognition:

- Template matching: statistical
- Syntactic matching: ANNs

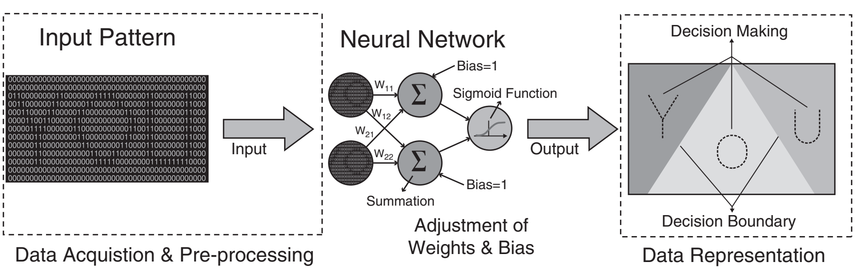

Figure 13.5 NN for pattern recognition.

Following NN architectures used for pattern recognition:

- Multilayer perception: Kohonen self-organizing map
- Radial basis function network
- ANN uses the processing of the brain as a basis to develop algorithms that can be used to model complex patterns and prediction problems.

6 Key Points Related to a Typical Network Architecture

- The network architecture has an input layer, hidden layer (there can be more than 1), and an output layer. It is also called MLP because of the multiple layers.
- The hidden layer can be seen as a "distillation layer" that distills some of the important patterns from the inputs and passes them onto the next layer to see. It makes the network faster and more efficient by identifying only the important information from the inputs leaving out the redundant information

7 Common Applications of NNs

ANNs due to some of their wonderful properties have many applications:

1 **Image Processing and Character recognition:** Given ANNs' ability to take in a lot of inputs and process them to infer hidden as well as complex, non-linear relationships, ANNs are playing a big role in image and character recognition. Character recognition like handwriting has a lot of applications in fraud detection (e.g. bank fraud) and even national security assessments. Image recognition is an ever-growing field with widespread applications from facial recognition in social media and cancer detention in medicine to satellite imagery processing for agricultural and defense usage. The research on ANN now has paved the way for deep NNs that forms the basis of "deep learning" and which has now opened up all the exciting and transformational innovations in computer vision, speech recognition, and natural language processing—famous examples being self-driving cars.

2 **Forecasting:** Forecasting is required extensively in everyday business decisions (e.g. sales, the financial allocation between products, capacity utilization), economic and monetary policy, finance, and stock market. More often, forecasting problems are complex, for example, predicting stock returns is a complex problem with a lot of underlying factors (some known, some unseen). Traditional forecasting models throw up limitations in terms of taking into account these complex, non-linear relationships. ANNs, applied in the right way, can provide a robust alternative, given their ability to model and extract unseen features and relationships. Also, unlike these traditional models, ANN doesn't impose any restrictions on input and residual distributions.

ANNs are powerful models that have a wide range of applications. Above, I have listed a few prominent ones, but they have far-reaching applications across many different fields in medicine, security, banking/finance as well as government, agriculture, and defense.

3 **ANN in business especially in finance**: NN has been used to predict risk in bankruptcy, using financial ratios as input data. The NN has also been used for bond rating, risk assessment of mortgages and loans, stock market prediction, and financial forecasting and analysis (Fadlalla and Chien-Hua, 2001).

4 **ANN**. **Used in the assets side** more than the liabilities side, as financial analysts pay more attention to managing assets over managing liabilities.

It is also used for credit analysis, underwriting analysis, and business cycle recognition.

All of these applications are common in unstructured and data intensive which involve much uncertainty, hidden relationships, and noise.

5 Coakley and Brown (2000): has also studied the applications of NNs in accounting and finance problems, they studied using NNs in managing investment by making predictions about debt and equity securities and also for credit advisors that used to grant instant credits for loan automobiles. Also, they used the applications of NNs in problems associated with accounting and auditing.

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