The revenue model of an online South African stockbroking platform

Wesley Ryan Bester

Student number: 2607202

Email: wesleybester.wb@gmail.com

Supervisor:

Euphemia Godspower-Akpomiemie, Ph.D.

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Abstract

As technology advances at an unprecedented pace, many businesses and industries must adapt to the increasingly digital world. The online stockbroking industry is no exception and requires significant attention and change to keep up with the times.

Business and revenue models in the stockbroking industry in South Africa have remained essentially unchanged over the past few decades. The variable-rate brokerage fee charged on transactions executed remains the primary source of income. This revenue model has rapidly become unsustainable with the decrease in these fees over the past few years. The study's main objective is to investigate revenue models that are more suitable for the digital trading environment. The study examines the background and appropriateness of alternative revenue models and platform models, along with the use of prospect theory to guide customer preferences.

This quantitative case study utilises secondary data from a South African bank's online stockbroking division, analysing over 334,000 trades over 10 years. The entire dataset is analysed by looking at its descriptive, and inferential statistics, as well as time-series analysis. The study investigates the relationship between frequency, transaction amount, and their effect on brokerage over time, along with their association using the Chi-square model. Secondly, a model is built to predict a fixed monthly subscription fee for clients to replace the outdated variable-rate brokerage model. Clients will then choose a model of best value to answer the second research question. The study addresses two hypotheses, it also finds brokerage fees highly correlated to transaction values and inversely related to trade frequency. Based on the results, the model developed can effectively predict future fixed monthly subscription fees for online stockbroking platforms.

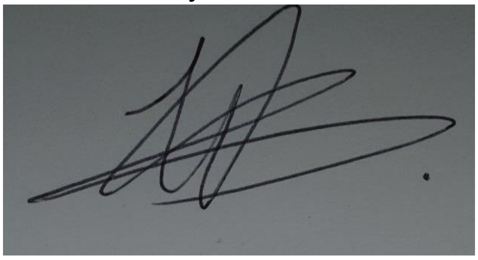
Keywords

Online trading, stockbroking, business model, revenue model, profit formula, platform-based models.

DECLARATION

I, Wesley Bester, declare that this research report is my work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Wesley Signature:



Signed at: Sandton.

On the 26th day of February 2024

DEDICATION

I dedicate this research to my supportive parents, siblings, friends, and colleagues who have fostered my growth and thirst for knowledge.

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I acknowledge with appreciation and thanks the following people:

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CHAPTER 1. INTRODUCTION

1.1 Purpose of the Study

1.1.1 Statement of Purpose

This case study examined the practicality of applying a new revenue model to the South African online stockbroking business model. Developing a revenue model aligned with a higher frequency of online trading can improve the way in which clients are charged. This case study showcases online investing platforms with alternative revenue models other than a purely traditional per-deal model, which only partially captures the new digital nature of trading. This case study employed a quantitative approach to assess the viability of an alternative revenue model.

1.1.2 Framework of a Traditional Brokerage Model

The framework of a traditional brokerage model in Figure 1.1 examines the challenges encountered in the stockbroking industry from a business standpoint. It aims to visually lead the reader through the issues and unique ideas presented in this research paper, and lays out the traditional model for brokerage charges, displaying the two main research problems, namely: competing through lower brokerage and not being geared towards digital channels. It proposes an analysis of historic deals to visualise trends in online brokerage rates, showing various influences while assessing whether a need exists for a new revenue model to address existing problems.

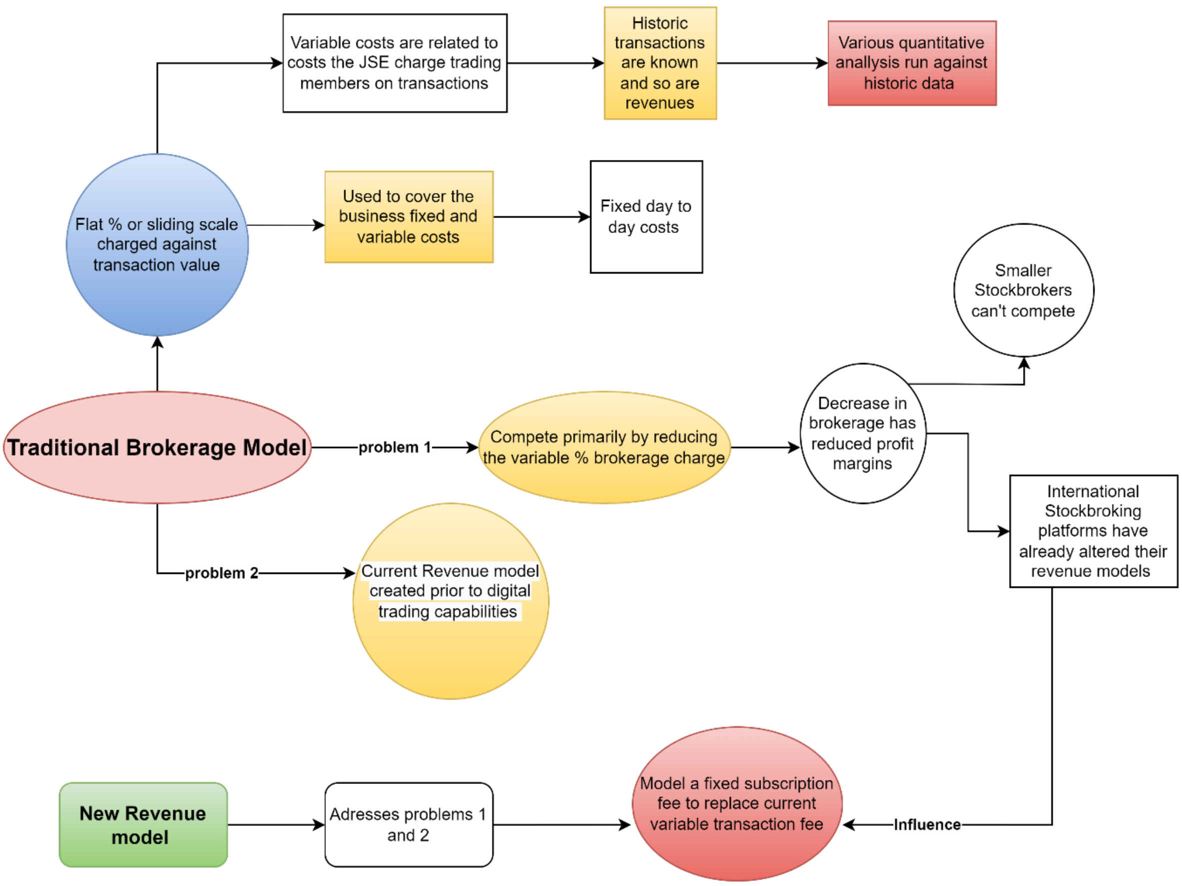

Figure 1.1: A brief view of the traditional brokerage model (Source: Author's compilation)

1.2 Context of the Study

As the world becomes increasingly digitally driven, customers prioritise providers who meet their changing needs, expectations, behaviours and accessibility (Fu & Mishra, 2022). This digital transformation and adoption trend has been accelerated by the COVID-19 pandemic, which affected various industries, including the financial sector (Kutnjak, 2021). The online stockbroking industry, in particular, experienced a surge in client growth, as investors preferred online platforms that catered to their needs (Ingrassia, 2021; Tan, 2021). According to Fu and Mishra (2022), the pandemic led to a remarkable surge in the daily downloads of finance-related apps, surpassing the typical growth rate by 21–25%.

South Africa is not excluded from this digital transformation in trading. South Africa's Johannesburg Stock Exchange (JSE) moved from an open outcry market, where retail client orders were communicated to their stockbrokers and executed on the exchange floor, to electronic trading. The JSE commenced its digital transition in 1996 when it switched to an electronic trading system (Dicle & Levendis, 2013). Willing parties exchanged the opposite side of the trade in a traditional floor-based trading system executed through verbal communication. The JSE electronic trading system was additionally supported in 1997 by a real-time news service. Reporting price information was followed by the adoption of the London Stock Exchange's digital order book, the Stock Exchange Electronic Trading Service (SETS) in 2002 (Dicle & Levendis, 2013). The Johannesburg Equities Trading system required orders to flow through the central order book unless the trade met specific off-book trading criteria[1]. The study by Dicle and Levendis (2013) regarding the JSE implementation of the SETS trading system showed evidence that trading activity almost doubled, and trading was more cost-effective. These are the results of digitalisation, with enhanced functionality for both retail and institutional investors.

The JSE was established on the 8th of November, 1887 and is Africa's oldest, largest and most liquid stock exchange (Lukasiewicz, 2019). The JSE follows an order-driven trading model and a limit-order trading system. The JSE is also included as one of the top 20 exchanges in the world using Market Capitalization[2]. The JSE's stability is essential for offshore investors, who comprise most of South Africa's daily trading volumes[3]. South Africa is highly competitive from an emerging market's perspective and earns 49% of its equity market revenues from foreign sales, ranking fourth behind Taiwan, Chile, and Korea, respectively[4]. Taking these matters into account, a South African online stockbroking platform will be used as a case study, which is sufficiently comprehensive from a global, emerging market and African perspective. Global trends will apply to South Africa, and the established exchange provides sufficient historical data for analysis.

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[1] Johannesburg Stock Exchange. (2023). Equity Rules, Rule 116.(page 44)(https://www.jse.co.za)
[2] South Africa Banking & Financial Services Report: (Q3- 2023). www.fitchsolutions.com/bmi
[3] *Annual Results Presentation* [Audited results, 9 March 2023]. www.jse.co.za
[4] Goldman Sachs. (2023). EM in Focus_ South African Equities - Weighing Domestic Risk Premium Against Better Fundamentals for Exporters

The JSE focuses on providing direct market access to clients through its members who follow the JSE regulations[5]. Client orders pass directly onto the exchange, matching buy and sell orders through the exchange central limit order book. Figure 1.2 provides a visual cue of the order flows on the JSE. There is a clear illustration of the relationship between buyers and sellers and how the JSE trading system matches these orders. The JSE accounting system records all transactions, before the JSE clearing system sends the details to STRATE, the clearing and settlement authority.

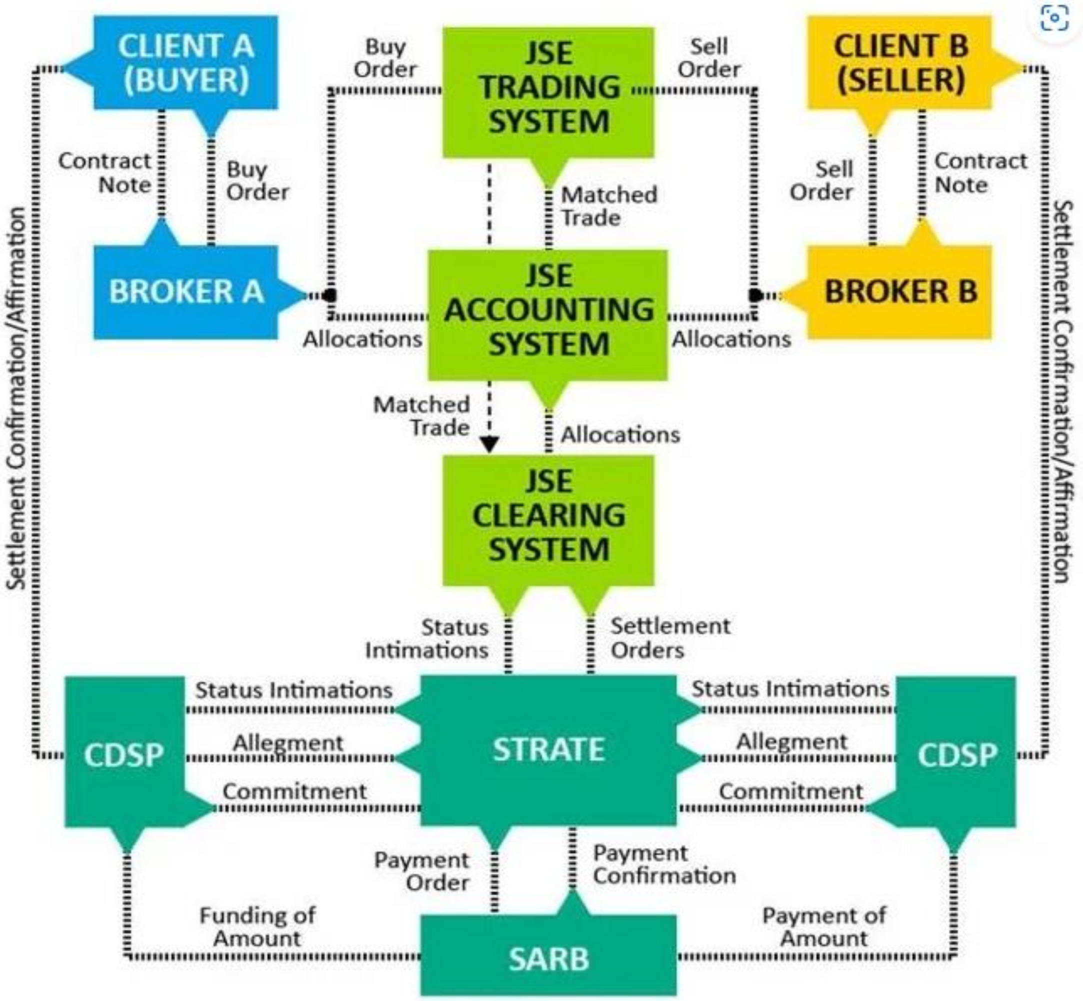

Figure 1.2: JSE equities market, order flow and clearing. (Source: Equities Operations | Johannesburg Stock Exchange (jse.co.za))[6]

[5] Johannesburg Stock Exchange. (2023). Equity Rules, Rule 116. (https://www.jse.co.za)
[6] Equities Operations | Johannesburg Stock Exchange (https://www.jse.co.za)

The South African online investing environment provides its clients direct market access to the exchange through the JSE's central limit order book. Orders are matched against those with the best price on the screen[7]. In this case study, the South African parameters of trading through the central order book will remain and the study will not follow international off-book trading flows. The focus is to modify or improve how clients pay fees to better suit all stakeholders involved. Clients are charged additional fees over and above brokerage fees, including minimum transaction fees and monthly platform admin fees. These fees vary between platform providers but only make up a small portion of the total revenue earned. As equity brokerage rates are the primary source of revenue for this researcher, only those rates are accounted for in this case study.

Transaction fees need to be considered by investors and traders alike and are likely to influence their choice of stockbroking provider. Woodside-Oriakhi et al. (2013) reviewed the various transaction costs applicable to executing financial assets and summarised them as fixed, variable, or a mixture of the two. Fixed costs are paid regardless of the transaction size, while variable costs are based on the transaction value (Woodside-Oriakhi et al., 2013).

Globally, there has been a shift, particularly in the United States (US), to attempt to democratise trading by applying a zero brokerage or commission fee to transactions executed through online investing platforms (Tan, 2021). These platforms charge higher interest on deposits and sell their order flows to wholesalers in the market in return for a share in the spread earned. There are additional service subscriptions for premium services or tools. Robinhood, one of the pioneers of zero brokerage trading, has recently gained popularity, albeit initially launched in 2013. Robinhood was the first to market with this idea and successfully implemented its solution on a large scale, while numerous other platform providers have only recently followed in their footsteps (Berkow, 2021). A deeper dive into Robinhood's successes and failures can illuminate where their model can be improved, mainly as pertaining to which aspects will and will not work in the South African environment. Important points need to be raised with regard to the various other fees that are charged as well as the end benefits passed

[7] Johannesburg Stock Exchange. (2023). Equity Rules, Rule 116.(page 44)(https://www.jse.co.za)

onto the clients of brokerage saved versus the increased spread which the client ends up paying for (Berkow, 2021; Chlistalla & Lutat, 2011).

Platforms such as Robinhood in the US market have primarily earned most of their revenue by receiving a share in the spread earned for their client's order flow (Dowdy, 2023). These client orders are routed to a wholesaler who executes the orders off-exchange and gives the clients a price slightly better than seen on screen. The revenue generated from sharing in the spread earned by the wholesalers can be much greater than the brokerage charged, as clients cross the spread between the bids and the offers (Ingrassia, 2021).

Business models outline how a business can create and deliver value to its clients (Teece, 2010). Looking deeper into the business architecture, Teece (2010) found that revenues and costs leading to profits are essential for enterprises to deliver value to their clients. The central theme is creating and delivering value to customers while making a profit. At the same time, Johnson et al. (2008) focus more on the customer value proposition that competing offerings do not address. The four key elements which should be integrated to form a comprehensive business model are customer value proposition, profit formula, essential resources, and critical processes (Johnson et al., 2008). Later in this research, the terms profit formula and revenue model are used interchangeably.

Revenue models are the blueprint for defining enterprise success with viable architectures for revenues and costs (Teece, 2010). Sources of revenue do vary over time and across industries, while technology has been aiding in reducing costs associated with information (Teece, 2010). The multiple revenue stream approach (Teece (2010) has seen online businesses following an extension to what the cinemas used to employ, with soundtracks being sold and additional memorabilia. Johnson et al. (2008) see the revenue model as part of the overall profit formula. The overall profit formula has four components: revenue model, cost structure, margin model, and resource velocity (Johnson et al., 2008). According to Johnson et al. (2008), the revenue model components can be viewed as the product of price and volume in its most basic form.

The digital era has changed various aspects of accessibility to the traditional stockbroking environment, making it more accessible, convenient, and affordable for retail investors to invest in the stock market. Online investing platform developments allow individuals to invest through personal computers, mobile devices, and tablets[8]. The increase in online investing has changed platforms' offerings by including mobile trading apps and linking them to investment communities, and social media where investors can learn from each other.

The rise of digital environments and the introduction of new models impact older business models, and change is required to survive this disruption. In an interview on disruption, Clayton Christensen touched on three innovations that affect a business's growth and, indirectly, its profit margin (Christensen, 2020). The efficiency innovation mentioned by Christensen, namely, 'when companies try to do more with less', is interpreted as reducing costs by improving practical efficiencies until a point. Efficiencies do not create new growth and will not outlast a decreasing profit margin. Significant disruptions have been brought on in this digital era in all sectors. Businesses that did not keep up with these changes, such as Eastman, Kodak and Sears, were leaders in their sector until such time as they failed to keep up with the times (Christensen, 2020). Businesses can be created by repositioning, developing new business models, or repackaging existing revenue models. This has been exemplified by successful companies such as Uber and Netflix, which have effectively addressed their customers' needs (Christensen, 2020).

Traditional stockbroking revenue models were primarily based on generating revenue from brokerage or fees, namely, a transaction-based revenue model and did not include other revenue sources. Additional services include investment and trading services such as advisory, management, commissions, custodian, and earning additional interest on various products[9]. These revenue models were traditionally based on execution on behalf of the clients, with lower volumes, added execution risk, and less frequency, and all managed through human interaction.

[8] FSCA Financial Sector Outlook Study 2022
[9] Equities Rules, 116 (2023) & Market Regulation | Johannesburg Stock Exchange (https://www.jse.co.za)

The rise of digital technology, and especially online trading platforms, has created a need for a new revenue model. Therefore, a change is needed, as all industries are undergoing significant changes caused by digitisation[10]. This study has tested and developed an alternative model to collect revenue from retail investing clients who use online platforms to execute their own trades. This case study examined South African online stockbroking platforms while drawing insights from international platforms. The author analysed secondary data and developed a new platform revenue model by forecasting a fixed monthly subscription amount and comparing it against the old variable costs for retail investing clients. The aim was to replace the lost profit margins experienced from diminishing brokerage charges.

1.3 Research Problem

The online stockbroking industry in South Africa faces a significant challenge in refining and changing its ways to charge clients for online platform execution services[11]. Traditional stockbroking revenue models were not designed for the increased competition of today's digital era, with online platform providers lowering brokerage charges to remain competitive[12]. Due to the high JSE exchange costs, South African online stockbrokers cannot profit from low-value transactions unless accompanied by significantly increased volumes[13]. Online stockbroker revenue models need to be updated to align with other digital platform revenue models, or potentially be left uncompetitive and outdated.

Profit margins earned by these online trading platforms are continually decreasing due to firms needing to reduce their brokerage to remain competitive. The reduced profitability further impacts the industry and the organisation by failing to attract top talent, who typically follow industries where profitability and earning potential are the highest (He, 2018). Based on this identified problem, two sub-problems emerged:

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[10] FSCA Financial Sector Outlook Study 2022
[11] South Africa's Security Dealing Sector 2020: Market Challenges Poised by COVID-19 Pandemic (yahoo.com)
[12] www.fitchsolutions.com/bmi (South Africa Banking & Financial Services Report Q3-2023, pg. 51)
[13] www.fitchsolutions.com/bmi (South Africa Banking & Financial Services Report Q3-2023, pg. 51)

The current problem online stockbrokers face is they primarily compete against each other by lowering their transaction-based brokerage rates. The question that remained unanswered is: How do online stockbroking platforms replace this loss in fees?

Secondly, traditional brokerage models, predating digital trading platforms, operated on lower volumes with a personalised touch, relying solely on phone or email for trade execution by a licensed broker.

Retail clients in South Africa use online stockbroking platforms to trade for themselves without assistance. Previously, a stockbroker was needed to execute these needs with no alternative. Since the digitalisation of the JSE in 1996, the way clients are charged through a transaction-based fee has remained the same, while online trading capabilities have changed considerably.

1.4 Research Questions

Based on the explained problems, the study's primary aim was to explore alternative revenue and business models for online stockbrokers better suited to a digital trading environment. The following research questions were developed accordingly:

Research question 1: What are the effects of trading frequency and transaction values on brokerage rates over time?

Research question 2: What are the differences between the subscription-based payment model and the existing transaction-based model on brokerage rates?

1.5 Significance of the Study

The findings of this research case study will assist existing online stockbroking platforms in South Africa in refining their revenue models and staying competitive while keeping their profit margins intact. This will also instil new entrants into the market with confidence, as they will be able to employ the updated platform revenue model. The research findings may also enable the regulators to fill in any gaps in legislation that might not have been considered for policy creation. Global literature covers early adopters of new revenue models in stockbroking, such as those by Robinhood, charging zero brokerage fees (Tan, 2021).

Moreover, the findings of this study will contribute to the academic literature on online stockbroking platforms and the various revenue models applicable in South Africa, which are currently limited. This study gauges the validity of platform models being applied to the online stockbroking industry in South Africa. Ultimately, attempting to implement the best-fitting model against historical revenue data to validate and confirm a change in the revenue model is necessary and possible.

1.6 Delimitations of the Study

This study is delimited as follows:

I. South Africa is geared towards on-exchange trading through the JSE's central order book; this premise was followed, and no off-exchange solutions were considered.

II. The scope of this study consisted of a new revenue model to predict fixed subscription fees that can be applied to online investing platforms in South Africa.

III. Regulatory changes during the study were not considered.

IV. Tax concerns are beyond the scope of this study and were not considered.

1.7 Definitions of Terms

The following are the definitions of terms and key concepts of this research study.

I. **JSE** – Johannesburg Stock Exchange, the primary exchange in South Africa.
II. **Business model** – This describes the architecture of how businesses create and deliver value to their customers and how they extract their share of the value (Teece, 2018).
III. **Revenue model** – This financial architecture defines how profits are made and extracts the value capture portion of the business model. Revenue models refer to how firms generate revenue within a business model (Penier et al., 2020).

IV. **A digital platform business** – This is described by Armstrong and Lee (2021) as using digital technologies to connect buyers and sellers, creating network effects, reducing frictions, allowing smoother transactions and externalising physical assets (pp 445-460). Digital platform businesses can either be in the form of industry, technology, or multi-sided platforms.

V. **Platform ecosystem participants** – The ecosystem has five main components. Firstly, the platform owner defines the purpose, the business model and how the platform is governed. Second, the complementors provide complementary offerings. Third and fourth are the buyers and the consumers. Last is the vehicle through which the platform is accessible. Platforms must ensure constant engagement, a continuous exchange of value and data, and constant feedback between all participants (Armstrong & Lee, 2021, pp. 472–478).

VI. **Online stockbroking platform** – This digital platform provides clients access to execute buy and sell orders through a secure platform.

1.8 Assumptions

I. This study assumes that competition in South African online investing platforms is based on brokerage costs charged against deal size and the volume of trading execution.

II. An assumption was made that the new revenue model can be statistically and financially tested by comparing it to historical data and modelling it to predict future trends.

III. The updated revenue model will benefit clients and platform providers. Clients will select the model with the best value.

1.9 Chapter Outline

Chapter 1 starts with the purpose of this study, which explores the idea of an alternative revenue model for South African online investing platforms. This chapter outlines the basics of a business model, described by Teece (2018) as an architecture of how businesses create value for clients and extract their profits. The background introduces the core themes contained in the study, including stockbroking, pricing, platform models, and international trends in stockbroking.

Chapter 2 consists of a systematic literature review, followed by Chapter 3, which describes the research methodology deployed. Chapter 4 presents the research findings and discusses these findings.

Chapter 5 presents the author's conclusions, various recommendations, and areas for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter follows a systematic approach described by Kitchenham and Charters (2007) as identifying, evaluating and synthesising the available research. This literature review examines available research in relation to the aim of this study. Relevant theories are explored to delve deeper into the primary aim of exploring alternative revenue models in stockbroking in South Africa. The background introduces relevant topics and themes to guide and address the research questions. Revenue models are discussed, with business models being crucial in choosing pricing mechanisms. International literature is reviewed for variety and reach, as well as South African literature, to guide the best-in-class approach when aligning the South African perspective. The review also focuses on digital platforms, the required ecosystems, and their relevance to the stockbroking industry. A theoretical overview of prospect theory (PT) is carried out, as well as its applicability to address the research question on customer decision-making behaviour. This chapter concludes with research question summaries, the literature's conceptual framework, and an analytical overview of connecting variables.

2.2 Background of the Study

The primary motivation of this study is to change how online stockbroking businesses charge clients in South Africa. The first sign of digitisation of the exchange in South Africa occurred in 1996 when the JSE transitioned towards being fully electronic for trading functionality (Dicle & Levendis, 2013). There is a need for South African online stockbroking platform providers to further develop, match and implement the relevant international best practices to remain relevant and competitive.

The JSE's automated trading system, now known as TradeElect, licensed by the London Stock Exchange, processes this order-driven market (Wyk et al., 2015). The JSE central order book accepts orders from investors through a registered JSE broker through TradeElect, where it matches automatically with an opposite order (Wyk et al., 2015). Globally, equity markets are considered vital in the financial system as a whole and are a critical source of finance in the real economy (Wyk et al., 2015). Equity markets are essential for the financial system, and the role of stockbrokers in facilitating a viable platform for clients' needs to be understood and geared towards long-term sustainability in the new digitally-driven environment.

South African Policy and Regulation

The Financial Services Conduct Authority (FSCA) oversees the regulation and supervision of the securities exchange of South Africa. Their aim is to ensure capital markets are efficient, fair, and transparent by providing a regulatory framework for stock exchanges to conduct business. This ensures investors can buy and sell shares in a conducive environment[14]. The FSCA sets the guiding framework of the Financial Markets Act 19 of 2012, which is the overarching requirement for stockbrokers to abide by, and which the JSE equity rules expand on[15].

The Financial Markets Act requires a stockbroker to be an authorised user and sets the standard on pricing and fees. This includes two rules: 1. Stockbrokers '*must disclose to their clients the fees for their services, which disclosure must give the specific monetary amount for each service rendered; or if such amount is not pre-determinable, the basis of the calculation'*. 2. Stockbrokers *'may charge a fee for different categories of transactions*. The JSE expands further on how stockbrokers' price their fees in terms of the JSE equity rules:

- A mutually agreed fee may be charged to the client in advance of such a transaction.
- Profits are to come only from agreed commissions or fees.
- In respect of a transaction other than the agreed commission or fee, full disclosure and accurate information about the fees and charges is required.
- Fees and charges are to be reflected in specific monetary terms.

International retail trading apps such as Robinhood have become immensely popular in the US, attracting both first-time and experienced investors. These new applications offer enhanced convenience and reduced trading expenses, which disrupt conventional brokerage business models by providing zero commissions (Tan, 2021).

[14] Financial Markets Act 19 of 2012
[15] Johannesburg Stock Exchange. (2023). Equity Rules, Rule 116.(https://www.jse.co.za)

Stock exchanges and brokers address the fundamental issues investors face by reducing information asymmetries by publishing prices, providing infrastructure, and matching buyer and seller transactions (Feyen et al., 2021). To stay competitive against big technology companies, financial institutions have had to embrace new technologies and break down the production of financial services to improve their efficiency (Feyen et al., 2021).

As equity markets become entirely digitally driven, updating business and revenue models will become vital to unlocking value and exploring the latest trends, such as platform business models. Platforms can be seen as intermediaries that allow and provide for exchange between participants who deploy the use of platforms (Goldfarb & Tucker, 2019). Platforms can monopolise supply- and demand-side economies of scale while pursuing a winner-takes-all position (Croxson et al., 2021). This study determines if the current traditional transaction-based pricing model for stockbroking platforms would be better replaced by a subscription-based model.

2.2.1 Introduction to Business Models

Historically, business strategy and traditional measures such as resourced-based views dominated the literature. During the past two decades, the literature has shifted to the business model as a unique concept spurred on by the growth of the internet and e-commerce (Teece, 2010). In the past, strategy theories that preceded business models, such as the resource-based view of the firm or its positioning, posited that value creation was only a result of producers and not customers. This approach focused on supply-side factors and a single competitive advantage (Barney & Arikan, 2005; Porter, 1996; Porter & Kramer, 2011).

A company's business model refers to the framework it uses to manage the critical aspects of providing value to customers, receiving payment for that value, and converting it into profit. This definition, coined by Teece (2010), encompasses a business's overall structure and strategy. According to various scholars, the value proposition of a company shapes its business model, including the manner in which it creates and captures value for its clientele (Massa, Tucci & Afuah, 2017). Teece (2018) further narrows down his reasoning on business models to focus on identifying the target customers and the methods of revenue generation. Strong dynamic capabilities, organisational design and business models work together and are seen as interdependent functions of each other for success (Teece, 2018). Teece (2018) considers the interactions between these as the central theme, where solid dynamic capabilities enable the effective implementation of business models.

Saebi et al. (2017) bring an adapted dimension into the business model literature, as the management adapts their business model to the changing environment. According to research, businesses tend to change their business models more readily in response to threatening conditions rather than perceived opportunities (Saebi et al., 2017). Depending on the perceived threat, these adaptions to the business model can be large or small.

Internal and external forces influence a business model's environment. Ramdani, Binsaif, Boukrami and Guermat (2020) summarise past literature elaborating on internal and external challenges. According to Ramdani et al. (2020), there are two internal challenges that affect the business model: top management and organisational culture. A business can face seven external obstacles that may impact its operations. These include crises, client demands, regulatory changes, advancements in technology, competitive pressures, and industry/service provider influences that affect the overall environment (Ramdani et al., 2020).

To provide clarity of underlying components within the business model, drawing from Schön (2012), a modular approach assists in graphically showing the interactions.

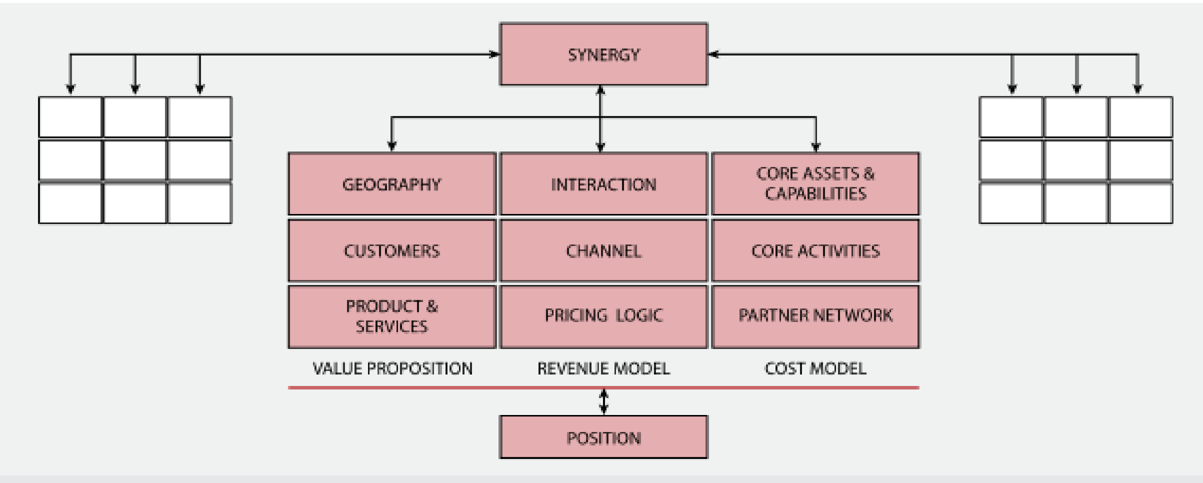

Figure 2.1: Capgemini Consulting Business Model Framework. (Source: Schön, 2012)

The linkages between the three central dimensions: value proposition, revenue model and cost model, are shown in Figure 2.1. In each dimension, relevant influencing factors, such as pricing logic and the specific channel to market within the revenue dimension, are linked to the overall synergy they produce (Schön, 2012).

The literature builds a foundation of how businesses and business models must be adapted from a broader perspective then just a single approach. David Teece pioneered the early thinking of business models in the digital era and separated these models from being termed strategy (Saebi et al., 2017). There can be minor or significant adaptations made to a business model depending on one's circumstance, as Saebi et al. (2017) posited, while Linnenluecke (2017) shows that sticking to one's core business model through all occasions can work. With the advent of digitisation, the stockbroking industry has undergone significant changes. A more drastic approach to the business model is necessary to remain relevant and meet customers' evolving needs. A redesign of the revenue model can address these needs.

2.2.2 Introduction to Revenue Models

According to Clauss (2017), businesses can capture financial value by exploring alternative revenue streams, adjusting their pricing strategies, and evaluating their profitability and sustainability. Clauss (2017) takes this one step further, where attention is drawn to changing business models by introducing new cost structures, particularly new revenue models. In a business model, the value capture aspect is determined by the revenue model applied to determine its financial success and by adjusting revenue streams and cost structures to be optimal (Vaska et al., 2020).

Ramdani et al. (2020) compiled an interesting study across numerous business divisions within the financial sector, and of particular interest is the asset management division within which stockbroking is a crucial activity. The value proposition is the essential dimension with notable important sub-dimensions, including revenue streams, where it was found fee-based models are the most dominant (Ramdani et al., 2020). The stock brokerage division responded to four challenges: new technology, crises, client demands and competitive pressure. It addressed them by deploying multi-brokerage models, charging clients trading commissions, and lending revenues (Ramdani et al., 2020). The revenue streams in the investment banking division were not consistent and were determined on a per-deal basis, including fixed fees, transaction-based fees, and success fees (Ramdani et al., 2020).

Vaska et al. (2020) relay a final finding on value capture, asserting that transaction-based revenue models are not viable for long-term application. If no further action is taken and transaction-based revenue is examined in isolation, Vaska and colleague's findings will be considered accurate according to this research study. The reality is that there will be slight adjustments made throughout the business's life cycle, as affirmed by Clauss (2017), who found that adjustments in some way or form should be made to impact either cost or revenue structures.

2.2.3 Introduction to Global Trends in Online Stockbroking

Recently, there has been a rise in retail trading activity due to the increasing popularity of financial technology (FinTech) apps used for investing, including Robinhood, a well-known US-based retail trading app (Tan, 2021). These new retail trading clients use apps such as Robinhood due to lowered trading costs and increased convenience, disrupting traditional brokerage models with zero-commission trades (Tan, 2021). This speaks to the US households reflecting their financial culture, which embraces more aggressive risk-taking and actively managing their investments (Fligstein & Goldstein, 2015). First-time investors rushed to join zero-cost platforms such as Robinhood to play the 'game' of speculation, with the platform's user-friendly interfaces and focus on user engagement, which lures them into this gamified trading space (Tan, 2021).

According to Lazaro and Verges' (2022) timeline, the impact of digitalisation on brokerage charges in the US is evident. The timeline reveals that with the emergence of day traders and a shift towards online trading, commission charges have now been reduced to zero, with 25% of trades now being conducted online. South Africa is a laggard regarding these global trends; the country is experiencing diminishing brokerage charges to remain competitive as online trading increases. However, South Africa has not reached zero-brokerage trading. Section 2.3 presents various themes that have the most significant impact on alternative revenue models in stockbroking.

2.3 Alternative Revenue Models in Stockbroking

The literature provides an overview of the challenges and applications that are particularly relevant to the revenue models in stockbroking. Several themes are highlighted, the most pertinent of which are expanded.

2.3.1 The Influence of Pricing

All businesses aim to create a price model that effectively entices customers to pay for their products or services. The price model should be configured to ensure a steady influx of revenue while delivering long-term value to the customers (Petri, 2014). In a study by Petri (2014), a slight change in the price model resulted in a radical shift in the business model itself. The evidence showed that changes could affect cash flow by shifting dimensions within the price model (Petri, 2014). According to Penier et al. (2020), a revenue model refers to how a business generates income. According to Penier et al. (2020), the earned revenue model involves providing a service and charging a fee to generate revenue for the business. Critical dimensions for a price model are clearly described by Petri (2014) in Figure 2.2, along with a description of the five key attributes.

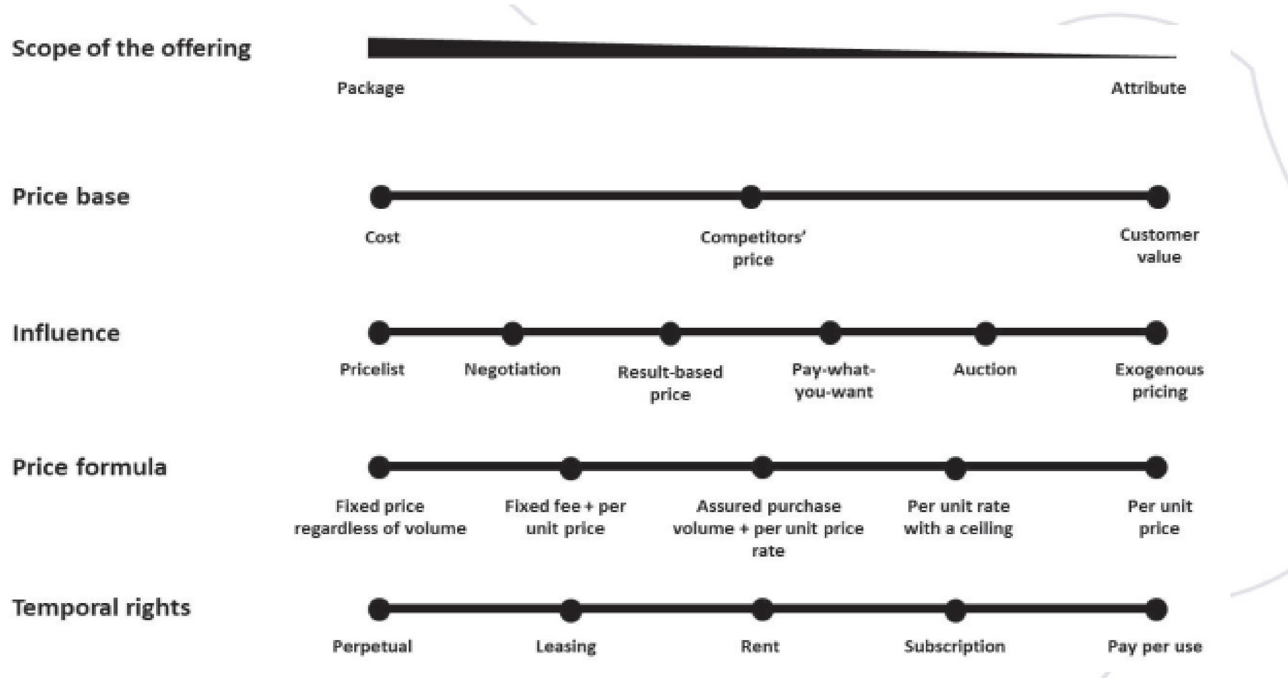

Figure 2.2: Five critical dimensions of configuring a price model. (Source: Petri, 2014, p. 5)

In Figure 2.2, the scope of the offering refers to either a single attribute being paid for, or a package of bundled items being bought together. The next dimension, the pricing base, was influenced by cost, and the customer or competitor information was used to price in the second dimension. The third dimension, influence, relates to buyer or seller negotiation over the price, with exogenous pricing beyond their control. The price formula connects volume and price and their specific combinations to determine a final price. The fifth and final dimension, temporal right, relates to the customer's time frame, with perpetual being the longest and pay-per-use the shortest. According to Petri (2014), the pricing in Figure 2.2 is a reliable and effective method for creating sustainable and profitable revenue streams, which can significantly improve the overall business model.

In transaction markets, platforms can generate revenue from people joining the platform and using it by sharing in the monetary value (Filistrucchi et al., 2014). Fees can be divided into two categories: transaction-based fees, which are simply transaction fees, and service-based fees, consisting of service, connection and membership fees (Kemppainen et al., 2018).

Modifying the price formula must be considered to address the research objective of whether an alternative revenue model is better than the traditional stockbroking brokerage model. A net monthly fixed subscription could be implemented as opposed to the current fixed fee plus a fee per transaction. This small change could have a significant impact on the industry. Petri (2014) states that to adjust the price model to have the desired effect, it should consider the overall business model and attempt to amplify and enhance its core features. Business models in resilient firms deal with challenges quicker, recover faster, and develop different or non-conventional ways of working while under pressure (Linnenluecke, 2017).

South African stockbroking businesses still in existence can be described as resilient firms, as defined by Linnenluecke (2017). Stockbroking fees in South Africa are primarily transaction-based fees, described by Kemppainen et al. (2018) as one of the primary categories of fees. Looking at Petri (2014) and the success achieved by changing the price formula, this could have the desired effect, namely, increasing the sustainability of online stockbroking platforms. The next theme presents digitalisation as a catalyst for global change, linking the traditional stockbroking business model poised for transformation and highlighting the importance of exploring alternative revenue models.

2.3.2 Digital Transformation and its Impact on the Financial Industry

The role of technological innovation in driving economic growth and industrial transformation is widely acknowledged. Rapid speed and constant evolution bring transformative changes (Gomber et al., 2018). Digital transformation harnesses new technology, allowing firms to capture value through platforms and improve customer relationships (Gomber et al., 2018). Vaska et al. (2020) identified four value creation dynamics brought on by digital transformation; the most relevant to stockbroking would be the revision and extension of existing services online and the offering of new value propositions precisely how clients want them. In the financial sector, disruptive technologies are employed against traditional business models to facilitate sustainability and harness the sharing economy (Vaska et al., 2020).

The cost of digital technology can impact economic actions, while digital economics aims to study how cost changes can alter economic models (Goldfarb & Tucker, 2019). Digital environments offer numerous benefits, such as reduced search costs, almost costless digital replication, individual behaviour tracking, and digital verification. These factors combine to create significant cost savings and improve overall economies (Goldfarb & Tucker, 2019).

Liu et al. (2011) described digital transformation or 'digitalisation' best by stating it as integrating digital technologies into business processes. This aligns with the problems outlined in Chapter One with stockbroking revenue models not accounting for the digital era. In today's digital world, businesses must utilise digital technologies and platforms to gather and integrate data in order to stay competitive in platform economies (Petrakaki et al., 2018). The goal of digital transformation is to enhance an organisation by initiating changes through communication, information, computing, and connective technologies (Vial, 2019). Daugherty et al. (2016) have stated that platform-based business models are the most significant change in the world since the 18th century Industrial Revolution.

South Africa, an emerging market economy such as Taiwan, allowed its first electronic trading through the exchange in 1996 (Dicle & Levendis, 2013). These two markets are good for comparative reasons across this study while looking to the US and Europe for best-in-class examples in the stockbroking industry. Lin et al. (2021) analysed the online stockbrokers in Taiwan, who first allowed an online electronic transaction on 17 October 1997, where the order rate only accounted for 0.02% of stock exchange transactions. Taiwanese's online stockbrokers comprised 53 firms in 2020, and their electronic orders accounted for 65% of overall market turnover, with commission-based transactions accounting for 60% of transactions and brokerage fees accounting for 70% of the overall revenue (Lin et al., 2021).

The study by Lin et al. (2021) discovered that many online stockbrokers offer brokerage discounts to entice customers, diminishing their overall efficiency value. FinTech has positively impacted the stockbroking industry, as brokers can now provide electronic trading and other valuable services. According to Lin et al. (2021), there has been notable growth in this area. The next theme explores how Robinhood, the global leader in online stockbroking platforms, became a market leader and disrupted traditional stockbroking models in the US.

2.3.3 International Stockbroking Platform Robinhood is Setting Global Trends

New technologies have made online trading more accessible for younger investors, democratising and revolutionising private retail investing and changing its ecosystem (Ingrassia, 2021). According to Tripathi and Rengifo (2023), the Robinhood Effect, which involves increased trading activity and stock holdings facilitated by the popular trading platform Robinhood and its fractional trading capabilities, has resulted in a significant influx of $53 billion in new investments into the stock market. In Chapter One, it was mentioned that Robinhood's zero-brokerage model is a critical factor in attracting investors. Robinhood sells its clients' order flow and receives payment to compensate for the revenue lost from not charging brokerage fees. A closer look at the payment for order flow is required for completeness.

Payment for order flow (PFOF) is the revenue earned by a broker-dealer (i.e., Robinhood Financial LLC) for routing information to a market maker (i.e., Citadel LLC) from their online stockbroking platform on their client orders (Ingrassia, 2021).

Platforms such as Robinhood receive trading revenue via PFOF, allowing them to charge zero brokerage on their client’s trades. This trend is also occurring with other major online platform providers, who are altering their traditional brokerage models to zero-brokerage models and finding alternate means to generate returns (Ingrassia, 2021). Robinhood declares its revenue through these streams: rebates from market makers and trading venues (PFOF), subscriptions, margin interest, stock loans, income generated from cash, and cash management[16]. Many trades made by retail investors occur off-exchange. In these cases, the broker's inventory is used to match orders, or they are sold to a wholesaler (Eaton et al., 2022). Retail trading that takes place outside of exchanges is known as dark pool or dark market trading. Such trades must be reported to the Financial Industry Regulatory Authority within a span of 10 seconds (Eaton et al., 2022).

A study by Pagano, Sedunov and Velthuis (2021) on the realised spread between the buying and selling prices based on Robinhood’s user activity showed that the greater the retail client participation, the more market quality and lower costs were achieved. The impact on share price is also higher with increased user activity in regular periods, showing their users can affect price, which indicates lower market quality (Pagano et al., 2021). According to a recent study by Pagano et al. (2021), the participation of retail investors in financial markets can significantly affect trading quality, especially during times of market stress. Hence, institutional investors and regulators must take note of this finding.

Other ways of addressing the expense of trading in the equity market include trading through additional or alternative exchanges that charge lower exchange fees, such as the Chi-X exchange in Europe (Chlistalla & Lutat, 2011). South Africa has also attempted to address these high exchange cost inefficiencies by starting three alternate exchanges: ZARX, A2X and the CPT exchange[17]. There has been no attempt to sell order flow in South Africa to market makers such as in the developed countries with higher transaction volumes and values. South African retail investors trade on-

[16] https://robinhood.com/us/en/support/articles/how-robinhood-makes-money/
[17] www.fitchsolutions.com/bmi (South Africa Banking & Financial Services Report Q3-2023, pg. 51)

screen through the JSE central order book and do not trade off-exchange through their brokers, who abide by the JSE member exchange rules[18].

Hypothesis 1:

There is no relationship between time periods, trading frequency and market conditions and their effect on brokerage rates.

To address the research question of whether an alternative revenue model will be better suited than the traditional transaction-based revenue model, hypothesis 1 is tested on the relationship between the time periods, trading frequency and market conditions. To test this hypothesis, the author analysed 10-year historical secondary data on time periods, trading frequency, transaction amounts, and brokerage rates.

2.4 Platform Business Models are Suitable for Stockbroking

The literature provides an overview of challenges and applications most relevant to different platform-based business models. Although numerous challenges are mentioned, the most significant are described below.

The author expands on the brief introduction to platform models provided in Chapter One's introduction and the background provided earlier in Chapter Two. In their book, Armstrong and Lee (2021) mentioned three major platform types to pay attention to: internal product platforms, industry (or technology) platforms and multi-sided market platforms (pp 445-460). Each platform type has a value focus area, internal or external, with upstream or downstream participation and various key success factors (Armstrong & Lee, 2021, pp. 472-478). The critical success factors highlighted here are ecosystem value opportunities, network effects, innovation and asset externalisation and frictionless transactions (Armstrong & Lee, 2021, pp. 445-478). The next platform model theme with relevance to stockbroking is the universal success factors which apply to all industries.

[18] Johannesburg Stock Exchange. (2023). Equity Rules, Rule 116. (https://www.jse.co.za)

2.4.1 Critical Success Factors of Platforms' Business Models

According to Rohn, Bican, Brem, Kraus and Clauss (2021), the network of participants on a platform and their information exchange interactions are the most important intangible assets for facilitating transactions. Creating value within a platform context involves leveraging the platform's technology and network externalities to facilitate connections between participants, whether on a business-to-business or consumer basis (Rohn et al., 2021). When determining the price structure of platforms, three factors come into play, namely: the relative size of cross-group externalities, the type of model used (subscription or payment-per-transaction), and whether or not the customer uses multiple platforms to complete the desired activity (Rohn et al., 2021). Figure 2.3 extends the three traditional business model factors, including start-up culture, platform architecture and the advocation of digital transformation to achieve success in a platform business model (Rohn et al., 2021).

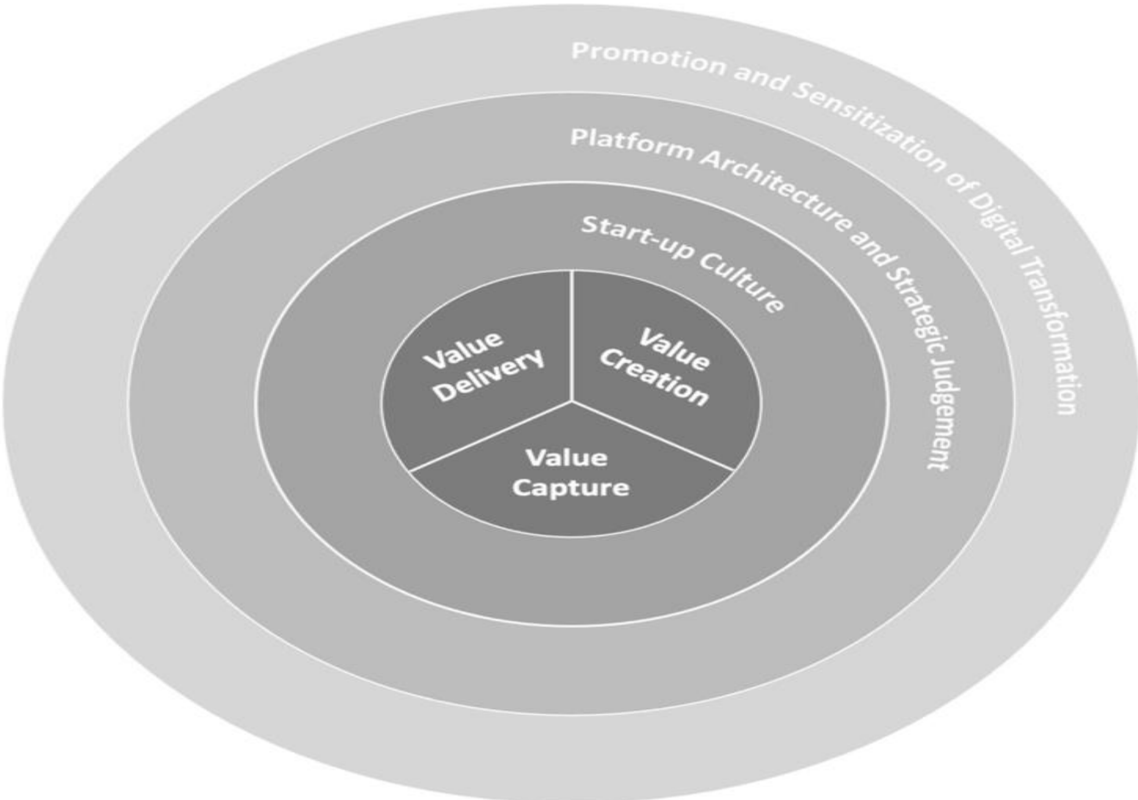

Figure 2.3: Critical success factors on platform-based business models. (Source: Rohn et al., 2021)

2.4.2 Network Effects

The network effect refers to the influence that a particular number of platform users have on the value generated by every new user, which can be either positive or negative (Parker et al., 2016). Stated differently using Metcalf's law, the value of the network grows non-linearly as the number of users of a network increases as users can now connect (Parker et al., 2016). Network effects are enhanced and exaggerated through frictionless entry and the ability to scale rapidly, maximising its value-building impact (Parker et al., 2016).

Network effects occur when at least two or more participants are connected to a platform to interact with one another (Rohn et al., 2021). Croxson et al. (2021) summed it up best, stating that greater market power and the ability to leverage this power come with the increased market size. Tipping effects can be used to build market momentum and, in so doing, achieve platform leadership (Armstrong & Lee, 2021). Looking at the stockbroking industry in South Africa, a community network effect has not yet been effectively taken advantage of by existing stockbroking platform providers.

Technology progression has threatened many industries' business continuity and rendered established business models obsolete, seeing new tech giants such as Amazon, Uber and Alibaba reorganising and renewing the market (Niemimaa et al., 2019). The world's most prominent players and giants such as Walmart and Target were forced to innovate their business models or fade into non-existence (Niemimaa et al., 2019). To achieve sustainability and success in platforms, certain factors must be considered. These include reaching a critical mass, facing competition, thriving in winner-takes-all markets, and fostering collaboration within business ecosystems. Ruutu et al. (2017) summarise that end users, developers, and service providers all form part of the requirements for gaining critical mass for self-sustaining growth and scaling a platform successfully.

Internet-based platforms have crucial roles regarding the applicability and use of data and the corresponding network effects of end users where data accumulation can be substantial (Ruutu et al., 2017). Specific South African stockbroking platforms can be seen as having already achieved a critical mass for survival. These internet-based platforms need to extract relevant data and focus on exploiting network effects from existing users to scale and grow exponentially. From this description, stockbroking platforms can be viewed as internet-based platforms.

2.4.3 Movement from Traditional Business Models to Platform Business Models

The dynamics of two-sided platform markets are shaped by various factors, including the platform's structure and the frequency and value of user transactions on the platform, and not solely determined by the fees charged (Rochet & Tirole, 2006). The swift expansion of FinTech and big tech companies into finance has led banks and financial institutions to adopt platform models to keep pace, utilising client data and automation to provide various third-party services tailored to multiple client groups and markets (Croxson et al., 2021). In platform markets, when more users are attracted, the average cost per user decreases, and the average return increases. The willingness of users to join a more comprehensive platform increases revenue (Croxson et al., 2021). Interoperability or multi-homing plays an important role, allowing users to interact with others on different platforms; even if just a particular group of users within a platform (Croxson et al., 2021). In financial services, this could entail using interoperable payment systems, which allows for excellent efficiency. The stockbroking industry could use different stock exchanges or various financial products on a platform.

The end user's willingness to transact on a platform is influenced by the platform's membership, usage, and variable and fixed charges, ultimately determining the end-user presence on the platform (Rochet & Tirole, 2006). Fixed fees such as membership or platform fees could be the most efficient way to capture end-user surplus; these fixed fees are in place to cover the platform's costs (Rochet & Tirole, 2006). Platform-based business models find that their primary income source is subscription fees (Croxson et al., 2021). This fee income closely fits the match-making business model, requiring little funding, balance sheet, regulation or supervision, with the core value coming from their network and data (Croxson et al., 2021). Online platforms can utilise their customers' data and advanced algorithms to determine everyone's reservation price and offer personalised pricing slightly below that threshold. This practice, known as 'value-extracting innovation', may be considered monopolistic conduct, according to Croxson et al. (2021).

Many financial institutions are transitioning from traditional business models to those used by FinTech and big tech companies. These financial institutions generate revenue through fees instead of relying on net interest income. However, this shift requires significant investment in digital technologies to collect and analyse big data to personalise offers, such as what big tech platforms do (Croxson et al., 2021). According to Croxson et al. (2021), platform-based banks now generate almost 40% of their revenue from fees and non-interest income, where previously their revenue was dominated by interest income as the sole source of banking revenue. In contrast, their peers are only extracting 33% from this avenue. This shift is attributed to these banks investing 50% more than their peers in technology, data processing, and communication as a percentage of their overall expenditure. Figure 2.4 displays banks with platform business models in red against competing banks with more total assets above 50 billion USD in blue.

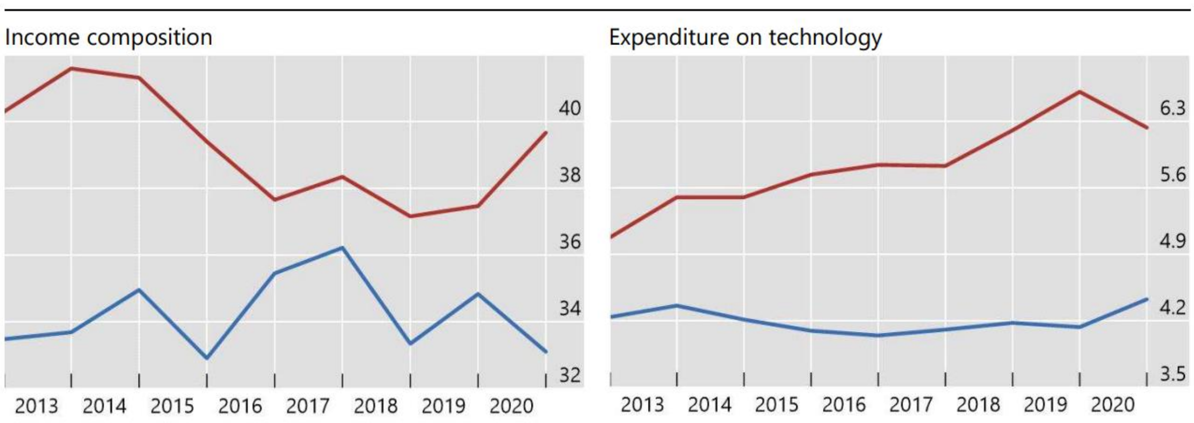

Figure 2.4: Revenue mix and technology investments in banks adopting platform models (Source: Croxson et al., 2021)

Looking at this global trend of adopting platform models, South Africa cannot be far behind and should consider adopting platform business models. As international financial institutions' structures change when they adopt platform models, this change is needed in the South African stockbroking industry to remain competitive. The author uses PT to determine if clients prefer a fixed monthly subscription-based pricing structure or the stockbroking industry's traditional fixed fee per transaction model.

2.5 Theoretical Framework

2.5.1 Application of Prospect Theory (PT)

In 1979, Kahneman and Tversky's research paper on decision-making under risk showed experimental proof of disregarding expected utility; their research is known as prospect theory (PT) (Barberis, 2013). This original work was updated in 1992, known as the ‘cumulative prospect theory’, and is still considered the best description of how people evaluate risk in experimental settings (Barberis, 2013). Kahneman and Tversky’s work was designed as a substitute for the expected utility theory, which did not consider how individuals make decisions in risk situations (Edwards, 1996). Barberis (2013) summarises the four critical elements of PT:

I. Reference dependence – used from gains and losses measured relative to a reference point.

II. Loss aversion – value function, where individuals are more sensitive to losses.

III. Diminishing sensitivity – value function towards a gain is concave and convex for losses.

IV. Probability weighting – overweight low probabilities and underweights higher probabilities.

Chang and Nichols (1987) use PT in their tax audit risk paper, demonstrating the applicability to payments and not merely income, where a tax payment can be perceived as a gain or a loss depending on the individual. In their research, Kőszegi and Rabin (2009) emphasise the significance of reference points and how they relate to loss aversion in PT. Specifically, they explore the difference between anticipated and realised consumption affecting reference points. Drake and Freedman (1993) found that extra time and effort are applied when a considerable percentage discount or savings are likely to be gained. Their finding presented an alternative perspective to PT, which asserts that an individual's decision is influenced solely by the percentage of the discount. A shortcoming identified by Edwards (1996) was that the predictive ability of PT found limited support in earlier work when applying the theory.

The author used PT to analyse user behaviour on a trading platform, comparing fixed monthly subscription and transaction-based pricing models to determine which one user's thought was of greater value. Alike to Chang and Nichols (1987), the author has shown that paying a fee structure that aligns with personal preferences can be advantageous for individuals and seen as a gain.

2.6 Conclusion of Literature Review

2.6.1 Summary of Findings on Alternative Revenue Models in Stockbroking

Digital technology must be embraced and adapted to the stockbroking business's unique environment. Adjusting the stockbroking business revenue collection method is essential to compete in this digital environment and to remain relevant. Robinhood has set the trend in the US, where zero-brokerage costs have become a way to compete with all major traditional brokerage houses following in their footsteps to remain competitive (Pagano et al., 2021). Petri (2014) shows that a slight change in pricing can have significant industry impacts.

2.6.2 Summary of Findings on Platform Business Models

While platform-based business models are new, there has been a definite trend towards their adoption from traditional business models across various industries. A common theme for successful platform businesses is the harnessing of network effects, externalising assets, exploiting big data, and a drive towards a winner-takes-all competition (Croxson et al., 2021; Rohn et al., 2021; Ruutu et al., 2017). The South African stockbroking industry is dominated by traditional banks, offering stockbroking as an additional service. Banks and financial institutions have globally adopted a platform-based business model (Croxson et al., 2021). The South African stockbroking industry should adopt a platform-based business model to remain competitive. The conceptual framework in Figure 2.5 outlines the key themes and concepts that have surfaced in the literature review. At the same time, the analytical framework (Figure 2.6) expands on the PT and variables that will influence and lead to a customer choosing a monthly subscription fee or not.

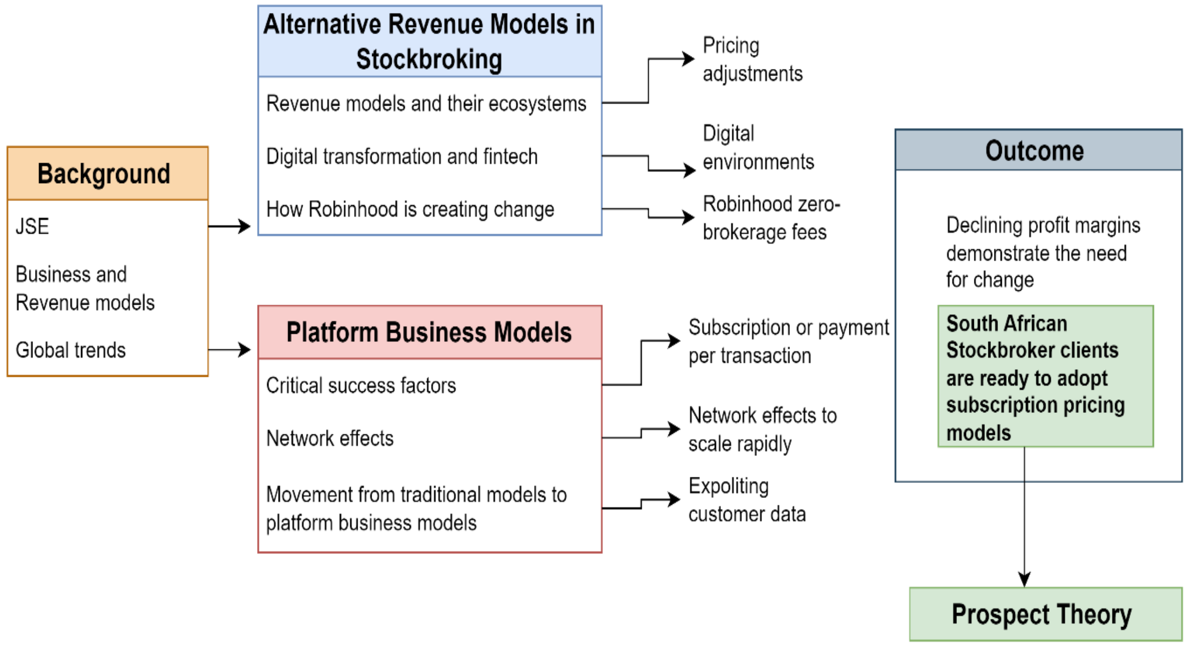

Figure 2.5: Conceptual Framework (Source: Author's compilation)

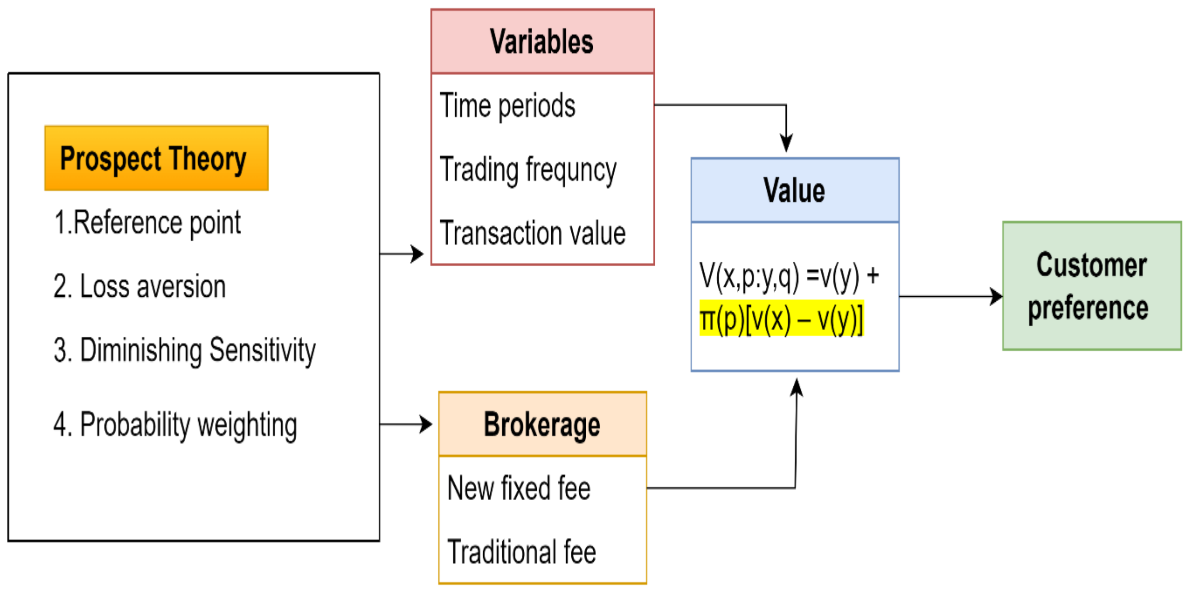

Figure 2.6: Analytical Framework (Source: Author's compilation)

Chapter 3: Research Methodology

3.1 Research Approach

This research adopted a case study approach from a quantitative perspective to address the primary research objective, namely: to assess the viability of alternative revenue models for stockbroking in South Africa. According to Creswell and Creswell (2018), quantitative research involves using numerical data to explore relationships between variables and develop and test theories (pp.38-47). The author used secondary data from a South African bank to analyse historic brokerage data and then mathematically model over a newly proposed subscription or fixed monthly pricing model.

The aim was to closely match the revenue generated from the traditional variable transaction-based model with a new fixed monthly subscription-based model. In this case study, the author adopted a positivist approach. This approach enabled a scientific and objective data analysis, essential for replication and generalisability, but which disregards subjectivity. This research has relied on systematic data collection, hypothesis testing through experimentation, and verification of results in alignment with the positivism paradigm (Grant & Giddings, 2002).

3.2 Research Design

This case study analysed the relationship between brokerage fees and independent variables such as time periods, trading frequency, and transaction value. The author used a cross-sectional design when performing descriptive and inferential analysis on data collected over 10 years from 2013 to 2023 in a South African bank. This case study followed a time-series design based on secondary data with no influence. Using correlation-based analysis to draw causal inferences with the help of logic assisted with comparing the actual observations and drawing conclusions (Edmondson & Mcmanus, 2007). This effectively addressed the primary aim of exploring alternative revenue and business models better suited to a digital trading environment. This research has encompassed experimental and descriptive research designs while concluding with a time-series analysis for completeness. Essential concepts focused on included validity and whether the research set out to measure what it intended to accomplish (Field, 2018, pp.15-16).

3.3 Data Collection Methods

A South African bank granted the author access to historical client brokerage and transaction data for stockbroking clients and brokerage fees over 10 years for the purpose of analysis. The dataset included actual brokerage data from client transactions, including trade execution time and frequency. All available brokerage data was initially extracted from a database running an SQL query, extracting available data in an Excel file for upload and evaluation in the IBM Statistical Programme for Social Sciences (SPSS) program. Brokerage fees per transaction were the primary variable extracted. The data was extracted and analysed in secured environments with no distribution or access to anyone other than the author.

3.4 Population and Sampling

3.4.1 Population

This case study was conducted on a South African bank focusing on its stockbroking division. Client characteristics included registered stockbroking accounts where clients executed shares themselves through the online platform (directly on the JSE while excluding ring-fenced clients belonging to third parties). This client database consisted of 334,000 online transactions starting from January 2013 and ending on 8 September 2023. The 10-year historical period aligns with when the business started growing its online stockbroking functionality and the financial industry became more digitally-driven and dependent.

3.4.2 Sample and Sampling Method

The author used the entire population as the sample, as the dataset was readily available for analysis upon extraction. The author implemented a census sampling design for the population of 334,000 transactions over the period to ensure precision, eliminate sample error, and explore relationships within subsets. Potential concerns with the dataset included issues of quality and population biases. The nature, quantum, and volatility of the daily trade data collected from 2013 to 2022 influenced the decision to group the data into yearly intervals and apply a cross-sectional design when analysing descriptive and inferential statistics.

3.5 Descriptions of Variables

The Chi-square test was used to measure the association between the dependent and independent variables and the difference between their expected and observed frequencies.

Chi-squared:

$$\chi^2 = \sum_{i=1}^{n} \frac{(O-E)^2}{E} \text{..........} \textbf{Equation 2}$$

Where:

χ^2 is the test statistic,

O is the observed value, and

E is the expected value.

Foundations of Prospect Theory: Understanding Client Choices

Exploring the Equation of Value Determination: Where V represents the ultimate value selected by clients, each decision is influenced by the probability (p) and the weighted decision factor π(p). Under the condition that p + q equals 1, the equation incorporates the relationship $x > y > 0$ or $x < Y < 0$.

$V(x,p:y,q) = v(y) + \pi(p)[v(x) – v(y)]$..**Equation 1**

Hypothesis 2:

There is no difference for South African stockbroking clients when choosing a payment option.

Using Equation 1 and adding a riskless component (remaining on the same brokerage rate) and a risky component (changing to a new subscription model) will predict a determinable value in the client's view. A new subscription-based model was based on the historical secondary data collected and analysed. Based on the client's current brokerage rate, PT values each hypothesis, and the client chooses the outcome with the highest value (V).

H2a: Stockbroking clients will prefer to pay a fixed monthly subscription.

H2b: Stockbroking clients prefer to pay a transaction-based fee per transaction.

Using the prospect theory (PT) discussed in Chapter Two, clients could choose between a new subscription fee or the old transaction-based model.

Based on PT, clients will choose the highest value (V), and each choice is the probability (p) and weighted decision $\pi(p)$ if $p + q = 1$, then $x > y > 0$, or $x < Y < 0$ (see Equation1).

Prospect theory is still considered one of the best measures when applying risk-based decision-making to determine an outcome (Barberis, 2013). Decisions for stockbroking clients were based on wealth or a cost reference point and were either accepted or not, depending on the new subscription-based fees (Edwards, 1996).

Prospect theory has limitations, as there is no precise answer as to what comprises a gain or a loss; the exact weightings are not defined (Barberis, 2013). Despite this limitation, a decision can be made once it is clearly defined where the greatest value lies for each outcome.

This research tested the following hypotheses:

The first hypothesis is tested using inferential analysis by way of conducting a Chi-square test using yearly data groups with a 5% significance level against the observed p-value.

Null Hypothesis 1: There is no relationship between time periods, trading frequency, transaction value, and their effect on brokerage rates.

The second hypothesis is tested by building a model that predicts fixed future brokerage fees at an individual client level and then compares those against historical actual fees.

Null Hypothesis 2: There is no difference to South African online stockbroking clients when choosing a payment option.

H2a: Stockbroking clients will prefer to pay a fixed monthly subscription.

H2b: Stockbroking clients prefer to pay a transaction-based fee per transaction.

3.6 Procedure for Data Collection

Stockbroking client data was originally saved on an underlying database immediately after each transaction. This research extracted stockbroking data by providing specific search criteria and downloading an Excel file through a front-end management portal. Permission to access and use the data was granted by the South African bank, with specific exclusions followed. This historically saved brokerage data was both cost-effective and easy to obtain. This data analysis used a licensed version of IBM SPSS statistics, version 28.0.1.0 (142).

3.7 Data Analysis Strategies and Interpretation

Descriptive statistics was applied as a base, as it is helpful in summarising data and describing the sample. However, it does not follow causal analysis (Fisher & Marshall, 2009). The distribution was determined according to different categories of time-series analysis, specifically linear regression and the auto-regression integrated moving average (ARIMA) model, which could present past observations, time points, and errors as a linear combination, with non-linearity being a weakness (Lee & Tong, 2011). A case study by Eisenhardt (1989) focused on a single setting, with the research steered towards that setting while understanding the various dynamics present. The following steps were taken in this order.

Firstly, the data was cleaned, and the dependent and independent variables were extracted. The historic brokerage data was analysed and compared using descriptive statistics to determine central tendencies and variances over time. After identifying consistent patterns in historical data through time-series analysis methods such as linear regression and the ARIMA model, which specifically consider seasonality and transaction size during high trading volume months, a distinct model using the most suitable approach was developed. The hypothesis was tested by proving the null hypothesis that there is no relationship between time periods, trading frequency and transaction value and their effect on brokerage rates. A Chi-square test of association was used to understand any association between the selected two variables, namely, dependent and independent variables. For the Chi-square model formula for descriptive and inferential analysis, see Equation 2.

Secondly, exploratory data analysis was performed on the already cleaned and analysed data to statistically model a new fixed monthly subscription model based on historic fee data. Additional variables, such as periods, trade activity (frequency), and market (economic conditions), were added to enhance the predictiveness of the model. ARIMA was applied to the model. Data was split into historical data and training sets for validity and generality tests, with periodicity of one-year intervals. The model was adjusted to accommodate the historic transaction-based fees. Once the model functioned as needed, it generated predictions for subscription fees. Model validation was performed by testing against a random selection of executed trades, ensuring accuracy and reliability. Time-series analysis was used to predict and forecast future values from the collected data.

Finally, using the PT discussed in Chapter Two, the client had a perceived loss or gain when choosing between traditional transaction-based fees or the newly modelled subscription-based fees. Figure 3.1 gives a graphical depiction of the outline.

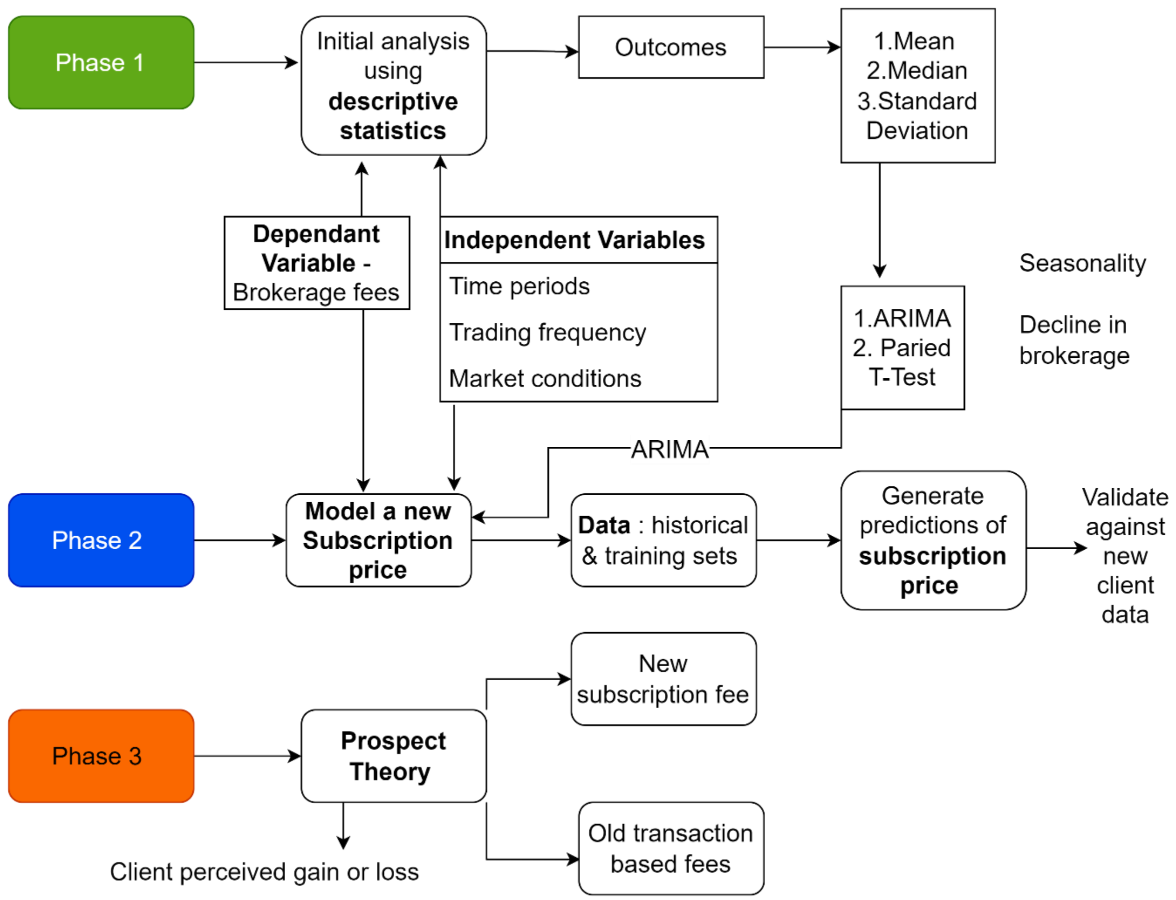

Figure 3.1: Diagrammatic outline of the modelling (Source: Author's compilation)

3.8 Possible Limitations and Challenges of the Study

I. Measurement on longitudinal case studies – varying time points can affect comparability.

II. Generalisability – even though it is a census case study sample (i.e., entire dataset obtainable used), these findings will be applied to the broader environment and industry.

III. ARIMA requires data to be stationary, requires parameter estimates, and the data must be sufficient and of high quality to drive the right results.

IV. If the initial hypothesis of a relationship between dependent and independent variables was false, indicating no association between them, would digitisation be a more significant motivator for online stockbrokers to adopt a platform model?

3.9 Quality Assurance

Analysis in the real world has brought about numerous complexities previously tested in perfectly controlled environments (Lincoln & Guba, 1986). The following quality assurances should provide reassurance that this research has considered its quality and is aware of the rigour required with its implementation and analysis.

3.9.1 External Validity

The research attempted to be generalisable and applicable to various scenarios while attempting to provide precise results on historical data with accurate future trends. The linear regression model and ARIMA model were used in order that comparisons could be made. The concern with the ARIMA method's inability to model non-linear data may pose a problem; however, linear regression proved to be more accurate and was used to complete the new model.

3.9.2 Internal Validity

Using a positivism approach, the author detected causal relationships in the data. Establishing a causal relationship with the historical dataset and the methods employed might be of concern; however, it was addressed by collecting data at varying time points, which solved the potential issue.

3.9.3 Reliability

The author ensured the findings could be replicated and dependable, providing consistent results[19]. This study used multi-item scales to ensure reliability. Cronbach's alpha addressed reliability with its function testing high commonalities, hence weak uniqueness. The function ranges between zero and one, with 0.7 and above being a good measure, indicating only a 30% potential error[20]. The reliability function of scales and Cronbach's alpha requires a minimum of three items per scale.

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[19] Sony, M. (2023). *Research Theory and Design – Quantitive approach.* Class slides and lecture notes

[20] Sony, M. (2023). *Research Theory and Design – Quantitive approach.* Class slides and lecture notes

3.10 Ethical Consideration

Data integrity, protection and anonymity were of utmost importance. The sensitive nature of the analysed and observed data necessitated assurance that neither the bank's name nor the client names were displayed.

A consistency matrix combines the research questions, its objectives and aligns the relevant data with the applicable analysis method in a concise table for easy comprehension. In the fourth chapter, the author shares discoveries and insights that correspond to the approach used in the consistency matrix methodology. These findings are further explored through in-depth discussions and interpretation.

Table 1: Consistency Matrix, objectives, data detail and analysis method

Main objective: Alternative revenue models in stockbroking in South Africa

Objective	Research Questions	Data Detail	Data Analysis Method
Alternative Revenue Models	Independent variable relationships with brokerage rates	A case study using historic brokerage data	Descriptive statistics
Alternative Revenue Models	Independent and dependent variable relationships with brokerage rates	A case study using historic brokerage data	Inferential analysis
Platform Business Models	Subscription-based fees	Case study data	Time-series analysis
Client Acceptance	Yes or no – risk-adjusted choice	Historic fees vs subscription-based fees	Prospect theory

CHAPTER 4: PRESENTATION, DISCUSSION AND INTERPRETATION OF RESULTS

4.1 Introduction

This chapter presents the results of the study in four parts to align with the consistency matrix presented in Chapter Three. Each of the four parts is presented with the observed results, interpretation, discussion, and summaries of the findings. The first section contains a descriptive analysis of the variables. The second part uses inferential analysis to determine whether the first hypothesis statements were met. The third section uses time-series regression analysis to determine a fixed subscription price. The last section presents ideas on whether clients would accept the new proposed fixed monthly subscription fee versus the existing variable-rate brokerage fees to answer the second hypothesis.

4.2 Data Cleaning

This secondary data, obtained for all client trades between 1 January 2013 and 8 September 2023, contained numerous fields and a total data point count of just over 11 million line items. Only the most important columns of data were kept, namely: client account number, transaction amount, brokerage amount, date, branch and deal sequence. All other columns were removed from the dataset. Transaction amounts for sales were originally presented as negative amounts, which were then converted to positive-only numbers using Excel's absolute function. Transaction amounts were also shown in cents and divided by 100 to convert into Rand amounts, giving a final transaction amount in Rands with only positive numbers labelled Absolute Tx amounts.

The website client data was the only data used after filtering out other branches. The deal sequence line was used to show the number of individual trades, which accounted for the total execution amount per deal per client. The brokerage amount, i.e., the fee charged by the online stockbroker, was captured in cents form and kept as such. All fields were limited to two decimal places. This data cleaning left 334,000 online stockbroking client deals from 1 January 2013 to 8 September 2023.

4.3 Descriptive Analysis and Interpretation

This descriptive analysis groups the extensive daily data into yearly intervals starting in January 2013 and ending in December 2022. A yearly cross-sectional view separately analyses the variables for annual independent observations.

To remain thorough and not be repetitive, the author has not interpreted and discussed all 10 periods, but instead focused on at least two tear intervals starting with periods for 2013, 2015, 2019, 2020 and 2022 to ascertain the impacts of COVID-19. Both absolute transaction amounts (Absolute Tx amounts) and brokerage amounts have been analysed. Transaction amounts were broken down into seven intervals, while brokerage amounts were broken down into five intervals. The volatile nature of the daily trade data collected required the data to be grouped into the most popular intervals. Observations were produced for each nominated year for transaction amounts and brokerage data, with results presented in either a table or figure.

4.3.1 Time Periods in Years – First Year 2013

4.3.1.1 Transaction amount for 2013

From the findings of this study, and as seen in Figure 4.1 for the base period 2013, transaction amounts indicate that the majority (15.7%) of the transaction values were formed in the interval 10154.49 – 18098.21. This percentage was followed closely by those observations in the 5306.85 – 10154.49 and 18098.21 – 32198.73 data intervals. The two second position intervals formed 15.5% each. The smallest percentage was created by the <= 2043.96 interval, which comprised 11.3% of the total. When six of the intervals were collapsed from 2043.96 – 5306.85, 5306.85 – 10154.49, 10154.49 – 18098.21, 18098.21 – 32198.73, 32198.73 – 76163.07 to 76163.07+ they formed the most significant majority percentage of 88.8%.

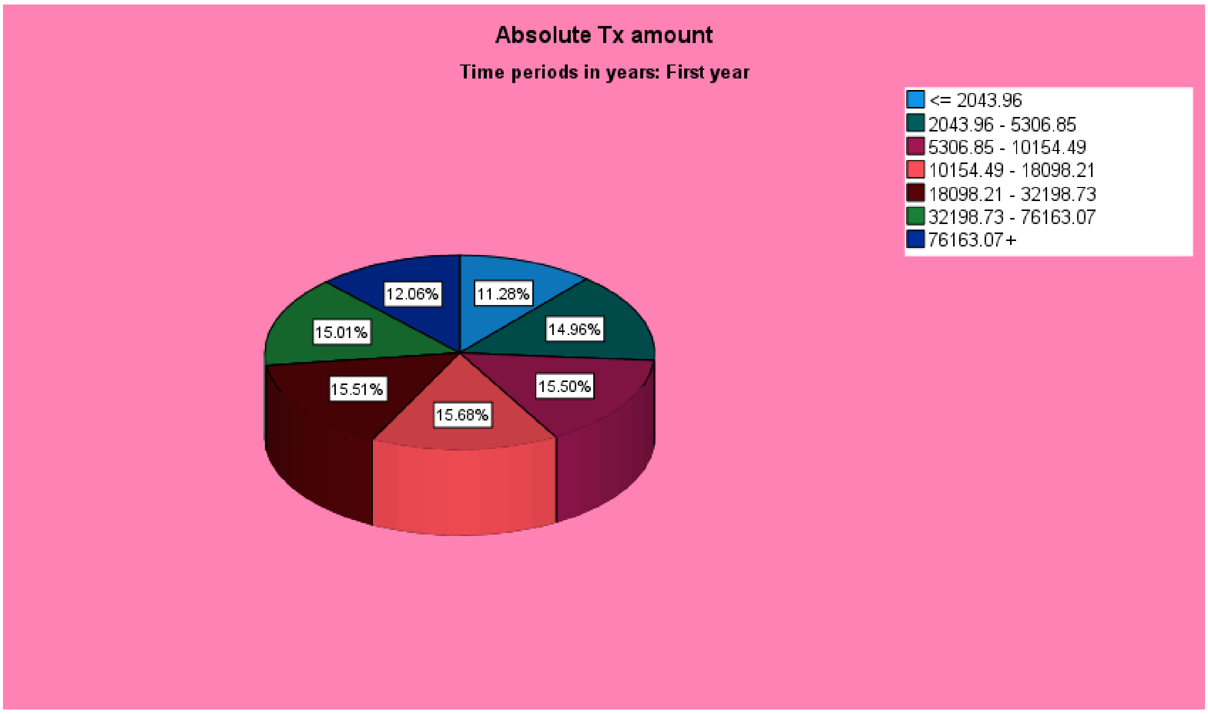


Figure 4.1: Absolute Tx amount for 2013

4.3.1.2 Brokerage Amount for 2013

The findings of this study shown in Table 2.1 indicate that most brokerage amounts were payments in the interval of <= 7000. This payment group formed 42.4% of the total. The most significant majority group was followed by the interval 8207 – 14980, which constituted 18.8%. The lowest representation from this statement comprised 5%. This group was formed at the 7001 – 8206 interval. Collapsing four of the groupings, namely, <= 7000, 8207 – 14980, 14981 – 33600 and 33601+, provides the highest percentage representation of the brokerage amount. This means that the highest brokerage amount arose from the collapse of four groupings, as indicated, accounting for 84.9% of the brokerage payment values.

The average of the highest brokerage amount constituted 23.75%, with an average brokerage amount of 19121.25. This figure is the observed average amount of the highest brokerage amounts and has been regarded as the base year 2013 average brokerage amount.

Table 2.1: Brokerage amount in 2013

Bins	Frequency	Percent	Valid Percent	Cumulative Percent
<= 7000	14 168	42.4	42.4	42.4
7001 – 8206	1 679	5.0	5.0	47.4
8207 – 14980	6 290	18.8	18.8	66.3
14981 – 33600	6 233	18.7	18.7	84.9
33601+	5 030	15.1	15.1	100.0
Total	33 400	100.0	100.0	

4.3.2 Time Periods in Years = Third Year 2015

4.3.3.1 Transaction amount for 2015

The data observations for 2015 are presented in Figure 4.2, which shows that most of the transaction amounts were transactions in the interval of 5306.85 – 10154.49. This transaction group formed 16.1%. This majority interval was followed by the 18098.21 – 32198.73 interval, which constituted 15.4%. The lowest representation from the year included 11.5%; this group was formed with the <= 2043.96 interval. Collapsing five of the groupings, namely, 2043.96 – 5306.85, 5306.85 – 10154.49, 10154.49 – 18098.21, 18098.21 – 32198.73 and 32198.73 – 76163.07, provided the highest percentage representation of the transaction amount. This means that the highest transaction amount arose from collapsing five groupings, as indicated here. The average of the highest transaction amount constituted 18.95%, with an average amount of 25296.60. This 25296.60 figure presented the observed average amount of the highest transaction amount for 2015.

Stock exchanges and brokers reduce information asymmetries by publishing prices, providing infrastructure, and matching transactions between buyers and sellers (Feyen et al., 2021). The adoption of online trading has slowly progressed observed in the study from the increasing average transaction amount of 25296.60 in 2015.The results in this study show online stockbroking platforms are making information and pricing increasingly transparent and, in turn, promoting trade. South Africa is closely linked to the global economy and exposed to external factors. The country's banking sector has remained stable despite fears of a worldwide recession. The electricity shortage and the ongoing load shedding affect confidence and growth in South Africa, pushing inflation expectations for the next year to peak at 7.4%[21].

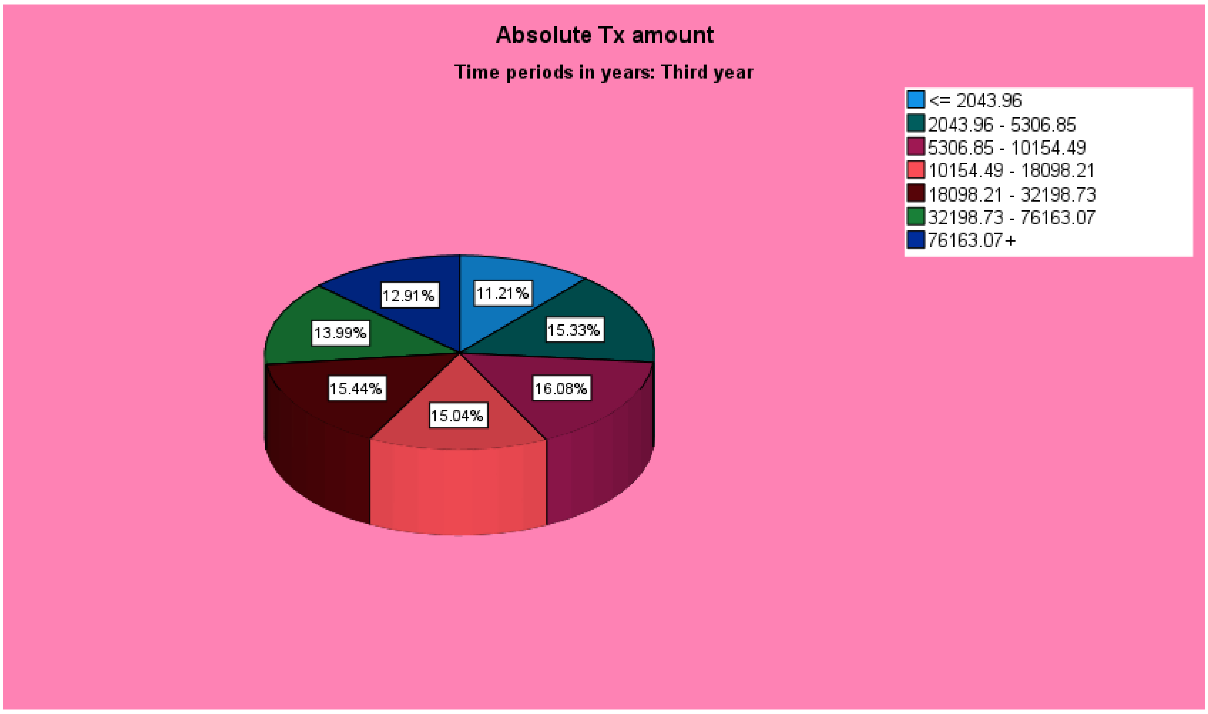


Figure 4.2: Absolute Transaction amount in 2015

4.3.3.2 Brokerage amount for 2015

The data observations in Table 2.2 show that most of the brokerage amounts in 2015 were payments in the interval of <= 7000. This payment group formed 45.8% of the total brokerage per executed deal collected for the year. The majority group was followed by the 8207 – 14980 interval, which constituted 17.9%. The lowest representation from this statement included 5.1%. This group was formed at the 7001 – 8206 interval. Collapsing four of the larger represented groupings, namely, <= 7000, 8207 – 14980, 14981 – 33600 and 33601+, provides the highest percentage representation of the brokerage amount. This means that the highest brokerage amount arose from the collapse of four groupings, as indicated here. The collapsed groupings represent 94.9% of the total.

[21] Fitch Solutions Company. (2015). Fitch South Africa Country Risk Report - Q4 2015 *Country Risk Report*

In comparison to the previous season, the brokerage amount for the year 2015 saw a decrease from the average of 19121.25 in 2013, which was associated with the highest brokerage percentage of 23.73%, to an average brokerage amount of 15947 in 2015. The 15947 figure is the observed average amount of the highest brokerage amounts for the period. Observing the data from this study, it revealed that there was a sharp drop in terms of brokerage amount from 19121.25 in 2013 to 15947 in 2015.

The slide in the stated amounts in 2015 of 15947 can be attributed to a reduced customer experience, as this area had not started to gain traction in Gartner's hype cycle for digital commerce. Gartner's hype cycle is a valuable framework to assess adoption and practical application of various technologies and used by firms as technology investment guides. Customer engagement hubs and customer journey analytics are identified as innovation triggers for the future in digital commerce (Daigler, 2015).

The South African economy only expanded by 1.3% in 2015, its slowest increase since the Great Recession. Business and household confidence measures weakened during 2015 to low levels, such as in times of crisis in years such as 2009 and 1993, exaggerated by a depreciating Rand currency exchange rate[22]. South African households are overstretched, with debt levels reducing slightly but still very high and savings rates in negative territory, indicating spending is exceeding income[23]. From the findings in this study, the author believed that the current state of the South African economy and households reflected the lower brokerage amounts for 2015 in retail online stockbroking.

Table 2.2: Brokerage amount 2015

Bins	Frequency	Percent	Valid Percent	Cumulative Percent
<= 7 000	15 313	45.8	45.8	45.8

[22] SARB. (2015). *South_African_Reserve_Bank_Annual_Report2015and16_Monetary_Policy*
[23] SARB. (2015). *South_African_Reserve_Bank_Annual_Report2015and16_Monetary_Policy*

7 001 – 8 206	17 05	5.1	5.1	51.0
8 207 – 14 980	59 74	17.9	17.9	68.8
14 981 – 33 600	55 45	16.6	16.6	85.4
33 601+	48 63	14.6	14.6	100.0
Total	33400	100.0	100.0	

4.3.3 Time Periods in Years = Seventh Year 2019

4.3.3.1 Transaction amount (a comparative analysis) in 2019

The findings of this study in Table 2.3 showed that most of the transaction amounts were payments in the interval of <= 2043.96. This payment group formed 16.5%. This majority interval was followed by the 2043.96 – 5306.85 group, which constituted 15.9%. The lowest representation from this statement included 12.4%. This group was formed at the 18098.21 – 32198.73 interval. Collapsing six of the groupings, namely, <= 2043.96, 2043.96 – 5306.85, 5306.85 – 10154.49, 10154.49 – 18098.21, 32198.73 – 76163.07 and 76163.07+, provides the highest representation of the transaction amounts. This means that the highest transaction amount arose from the collapsing of six groups, as indicated here. The average of the highest transaction amount constituted 15.14%, with an average amount of 27998.69. This figure presents the observed average amount of the highest transaction amount for 2019.

These estimated amounts were the highest compared to all the years' transaction amounts determined from the provided data from 2013 through 2019. This steady economic improvement could be based on established economic planning with positive strategic implications, influencing higher transaction values. The author further identifies a relevant study which took place in Vietnam. The case study aimed to determine the relationship between capital structure and performance of securities brokerage firms (Tien, 2023). The results recognised an intrinsic arrangement that significantly affects performance through the following variables: (1) financial leverage of a stockbroker, and (2) brokerage company size. The author believes these variables were in the control gear in the 2019 higher transaction value setup in South Africa and again in another developing economy as seen in Vietnam (Tien, 2023).

Table 2.3: Transaction amount 2019

Bins	Frequency	Percent	Valid Percent	Cumulative Percent
<= 2 043.96	5 397	16.5	16.5	16.5
2 043.96 – 5 306.85	5 227	15.9	15.9	32.4
5 306.85 – 10 154.49	4 569	13.9	13.9	46.3
10 154.49 – 18098.21	4 202	12.8	12.8	59.1
18 098.21 – 32 198.73	4 054	12.4	12.4	71.5
32 198.73 – 76 163.07	4 307	13.1	13.1	84.6
76 163.07+	5 043	15.4	15.4	100.0
Total	32 799	100.0	100.0	

4.3.3.2 Brokerage amount for 2019

The findings in this study in Figure 4.3 showed that most of the brokerage amounts were payments in the interval of <= 7000. This payment group formed 49.3% of the total brokerage for the year. This majority group was followed by the 33601+ interval, which constituted 17.7%. The lowest representation from this statement was 3.7%. This group was formed at the 7001 – 8206 interval. Collapsing four of the larger groups, namely, <= 7000, 8207 – 14980, 14981 – 33600 and 33601+, provides the highest percentage representation (96.3%) of the brokerage amount. This means that the practical highest brokerage amount arose from the collapsing of four groups, as indicated here. The average of the highest brokerage amounts constituted 24.075%, with an average brokerage amount of 18729.17. This figure is the observed average amount of the highest brokerage amounts.

Emerging markets experienced challenging market conditions in 2018, including slowing global trade, weaker commodity prices, and the appreciation of the US dollar. There was a better reception to the stabilisation of the economy in 2019[24]. The author observed a slight improvement in economic stability in 2019, leading to increased investor confidence and a rise in the average brokerage to R187.29. The positive net international investment over the past year boosted the South African economy, accounting for almost 11.6% of GDP in the fourth quarter[25]. The author believes

[24] South African Rereve bank. (2019). Annual-report-2018-2019- SARB. *Annual Report*
[25] South African Reseve Bank. (2019). Annual-report-2018-2019-SARB. *Annual Report*

foreigners could have influenced the positive performance of certain stocks, attracting more buyers and, in turn, increasing the average brokerage rate to R187.29 seen in the results.

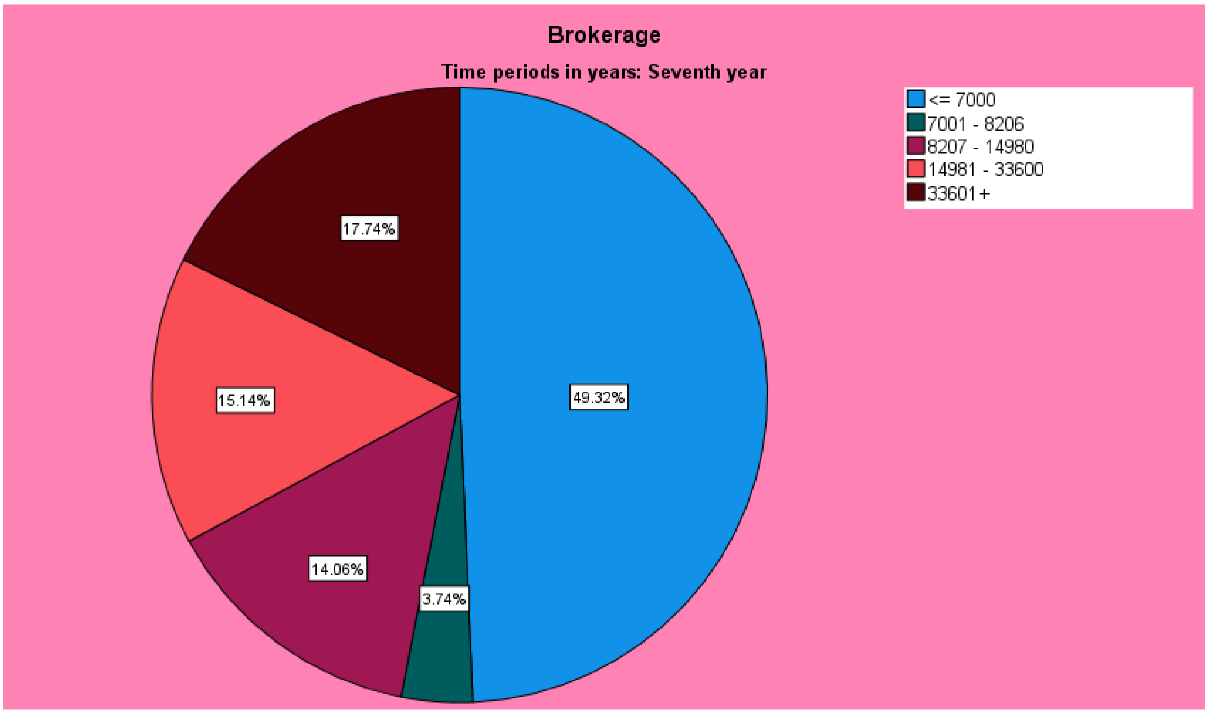


Figure 4.3: Brokerage data for 2019

4.3.4 Time Periods in Years = Eighth Year 2020

4.3.4.1 Transaction amount for 2020 (COVID-19)

COVID-19 influenced the findings of this study for the 2020 year displayed in Figure 4.4, which showed that most of the transaction amounts were payments in the interval of <= 2043.96. This payment group formed 16.5%. This majority interval was followed by the 76163.07+ group, which constituted 14.8%. The lowest representation from this statement was 13.3%. This group was formed at the 5306.85 – 10154.49 interval. Collapsing five of the groupings, namely, 2043.96 – 5306.85, 5306.85 – 10154.49, 10154.49 – 18098.21, 18098.21 – 32198.73 and 32198.73 – 76163, provides the highest percentage representation of the transaction amount. This means that the highest transaction amount arose from collapsing five groupings, as indicated here. The average of the highest transaction amount constituted 14.43%, with an average amount of 30072.20. This figure presents the observed average amount of the highest transaction amount for 2020.It is the view of this researcher that the 2020 transaction amount was the highest among all transaction amounts so far estimated from the given data. Establishing the conditions that led to this exemplary performance is necessary.

Ramdani et al. (2020) mention that a business can face seven external challenges that can impact its operations. The author highlights several factors that have significantly impacted the stockbroking industry in recent years. These include crises such as the COVID-19 pandemic, changing client demands for all-in-one solutions, competitive pressure on brokerages from low-cost and zero-cost platforms such as Robinhood, technological advancements, and the growing influence of service providers such as FinTech start-ups. All these factors have influenced the overall environment of the industry. To stay competitive against big technology companies, financial institutions have had to embrace new technologies and break down the production of financial services to improve their efficiency (Feyen et al., 2021). The trend will continue and needs to be considered for traditional online stockbroking platforms to survive. First-time investors rushed to join zero-cost platforms such as Robinhood to play the ‘game’ of speculation, with the platform’s user-friendly interfaces and focus on user engagement, which lures them into this gamified trading space (Tan, 2021). The author agrees that global lockdowns and the external challenges faced by the stockbroking industry drove the need for change in retail investing clients.

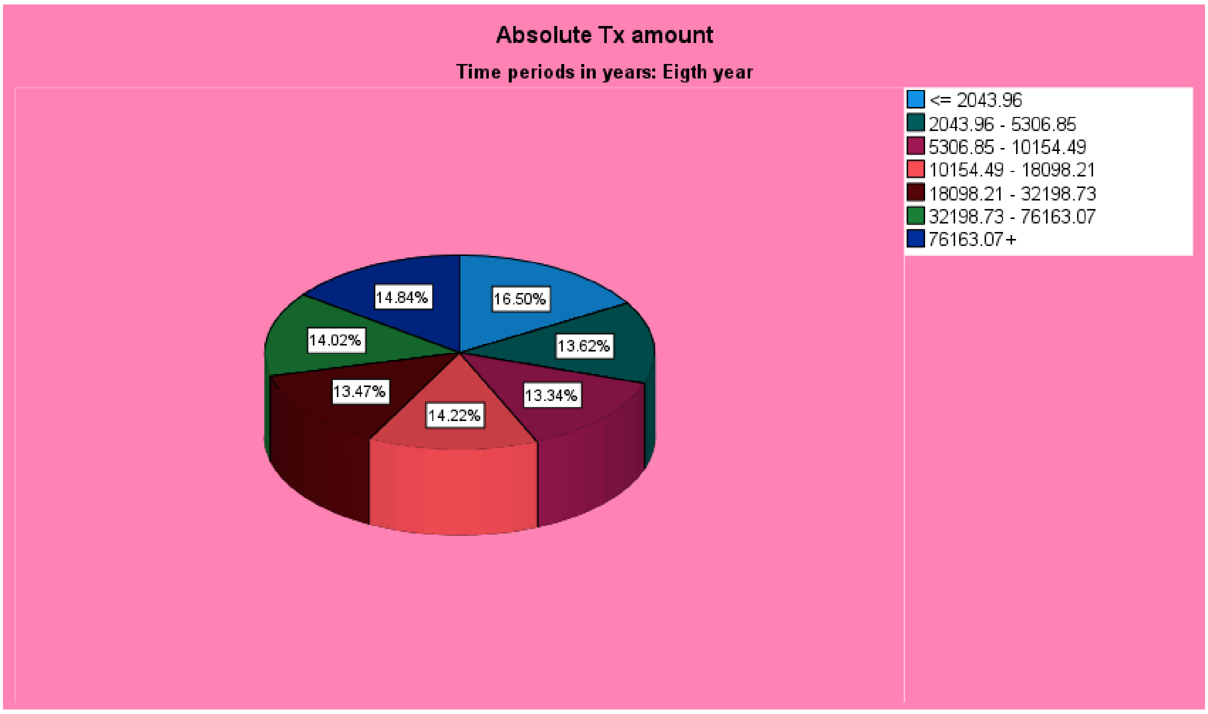


Figure 4.4: Transaction amounts for 2020

4.3.4.2 Brokerage amount 2020 (COVID-19)

COVID-19 influenced the findings in this study in 2020. Table 2.4 shows that most of the brokerage amounts were settlements in the interval of <= 7000. This payment group formed 47.4% of the total brokerage for the year. This mainstream group was followed by the 33601+ interval, which constituted 18.2%. The lowest representation from this statement was 4.1%. This group was formed at the 7001 – 8206 interval. Four groupings, <= 7000, 8207 – 14980, 14981 – 33600 and 33601+, provided the highest percentage representation of the brokerage amount. This means that the highest brokerage amount arose from the collapse of four groups, as indicated here. The average brokerage amount constituted 23.96%, with an average brokerage amount of 18928.17. This figure is the observed average amount of the highest brokerage amounts.

The South African Reserve Bank (SARB) cumulatively lowered the repurchase (REPO) rate by a cumulative 275 basis points between March and June of 2020 to combat the impact of the COVID-19 pandemic[26]. South African households benefited

[26] South African Reserve Bank. (2021). Note on the changes in bank deposit and lending- 2021 (SARB). *Quarterly Bulletin*

comparatively more than South African corporates on an effective yield basis. The government instated a national lockdown to curb the spread of COVID-19[27]. The author sees this as a significant driver in the increased average brokerage amount of R189.28, slightly higher than the 2019 average brokerage amount, which was already recorded as the highest in the analysis period. The author feels this could relatively explain the higher brokerage and transaction amounts in 2020 despite the blow to the global economy caused by COVID-19 and the international lockdowns.

Table 2.4: Brokerage amount in 2020

Bins	Frequency	Percent	Valid Percent	Cumulative Percent
<= 7 000	15 816	47.4	47.4	47.4
7 001 – 8 206	1 382	4.1	4.1	51.5
8207 – 14 980	4 746	14.2	14.2	65.7
14 981 – 33 600	5 374	16.1	16.1	81.8
33 601+	6 083	18.2	18.2	100.0
Total	33 401	100.0	100.0	

4.3.5 Time Periods in Years = Tenth Year 2022

4.3.5.1 Transaction amount for 2022

The observations of the findings of the study in Table 2.5 show that most of the transaction amounts were payments in the <= 2043.96 interval. This payment group formed 20.4% of the total for the year. This majority interval was followed by the 76163.07+ group, which constituted 16.4%. The lowest representation from this observation included 12.1%. This group was formed at the 5306.85 – 10154.49 interval. Collapsing six of the groupings, namely, <= 2043.96, 2043.96 – 5306.85, 10154.49 – 18098.21, 18098.21 – 32198.73, 32198.73 – 76163, and 76163.07+, provides the highest percentage representation of the transaction amount. This means that the highest transaction amount arose from the collapsing of six groupings, as indicated here. The average of the highest transaction amount constituted 15.14%,

[27] SARB. (2020/2021). South_African_Reserve_Bank_Annual_Financial_Statements_2020/2-21

with an average amount of 27458.32. This figure presents the observed average of the highest transaction amount for 2022.

New retail trading clients use apps such as Robinhood due to lowered trading costs and increased convenience, disrupting traditional brokerage models with zero-commission trades (Tan, 2021). The author recognises the ease with which these international trading platforms such as Robinhood can capture local South African retail investors and form a benchmark for their decision-making criteria when choosing an online stockbroker. The study by Lin et al. (2021) discovered that online stockbrokers offer brokerage discounts to attract customers, which reduces their overall value and efficiency. The author further believes this brokerage reduction incentive to attract customers has been driving the South African online revenue models closer to those of international rivals such as Robinhood, with zero commission being charged on trades.

Table 2.5: Transaction amount in 2022

Bins	Frequency	Percent	Valid Percent	Cumulative Percent
<= 2 043.96	6 808	20.4	20.4	20.4
2 043.96 – 5 306.85	4 662	14.0	14.0	34.3
5 306.85 – 10 154.49	4 055	12.1	12.1	46.5
10 154.49 – 18 098.21	4 062	12.2	12.2	58.6
18 098.21 – 32 198.73	3 920	11.7	11.7	70.4
32 198.73 – 76 163.07	4 412	13.2	13.2	83.6
76 163.07+	5 481	16.4	16.4	100.0
Total	33 400	100.0	100.0	

4.3.5.2 Brokerage amount for 2022

The findings for this study, displayed in Figure 4.5, showed that most of the brokerage amounts were payments in the interval of <= 7000. This payment group formed 50.4% of the total for the year. The majority group was followed by the 33601+ interval, which constituted 18.7% of the total. The lowest representation from this statement was 3.7%; this group was formed at the 7001 – 8206 interval. Collapsing four of the groupings, namely, <= 7000, 8207 – 14980, 14981 – 33600 and 33601+, provides the highest percentage representation of the brokerage amount. This means that the highest brokerage amount arose from the collapse of four groupings, as indicated here.

The average of the highest brokerage amount constituted 24.08%, with an average brokerage amount of 18247.17. This figure is the observed average amount of the highest brokerage amounts. The average brokerage amount of 18247.17 for the last calculated year shows that, on average, the online stockbroker has been performing well on average.

The South African economy grew by a modest 2% during 2022, with significant headwinds being load shedding and its intensifying schedule[28]. The SARB has increased the repo by 4.75% from November 2021 to May 2023, primarily aiming to control inflation[29]. The increasing interest rate cycle and continued growth headwinds faced in the South African economy could have influenced the reduced average brokerage amount of R182.47. Major global influences, such as the war in Ukraine, added pressure to the already struggling post-pandemic global economy[30]. The author believes this was another reason emerging markets such as South Africa saw net outflows from international investors compared to 2020, as discussed in that particular year.

[28] South African Reseve Bank. (2022). Full-Annual-Report-2022-23- SARB
[29] South African Reseve Bank. (2022). Full-Annual-Report-2022-23- SARB
[30] South African Reseve Bank. (2022). Full-Annual-Report-2022-23- SARB

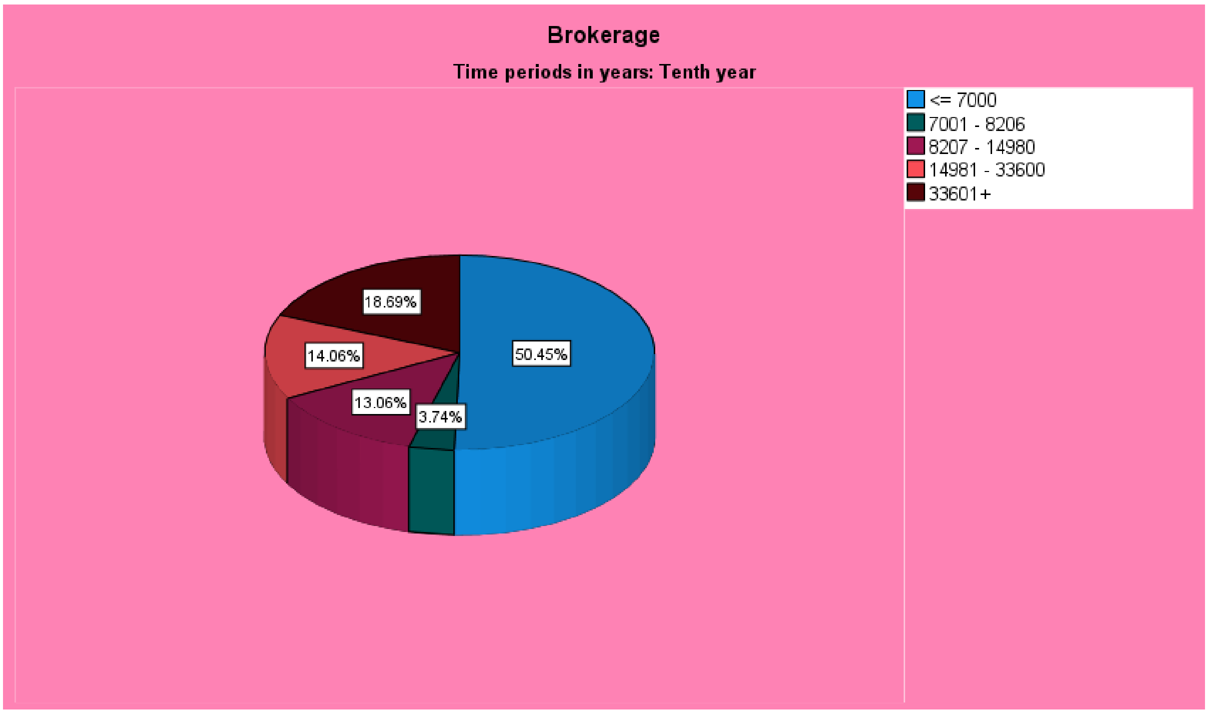


Figure 4.5: Brokerage data in 2022

4.3.6 Summary of Descriptive Analysis

The results showed that the five brokerage intervals were heavily skewed towards values of 7000 or less in each of the 10 years analysed. This interval consistently accounted for between 40% and 51% of all brokerages yearly over the 10-year analysis period. Most brokerage values were found by collapsing four of the five brokerage intervals, accounting for most of the brokerage values in a particular year. In contrast to this observation, transaction amounts were evenly distributed across seven intervals. There was not one observation where a single interval accounted for more than 20% of the transaction values over that period. It was further observed that to account for most transaction values in a particular year, up to six of the seven intervals for a specific year would need to be collapsed. While the brokerage amount charged had a skewed profile towards a smaller flat brokerage fee of R70.00, the transaction value profile was smooth and evenly distributed across the seven intervals.

Clearly, the findings of this descriptive analysis draw insights from both the South African economy and global observations documented in prior literature across diverse domains. Factors influencing the observed trends encompass the impact of the COVID-19 pandemic in 2020, international investors' net buying activity in South

African shares, sluggish economic growth, and the scale and size of the online stockbroking firm, all of which contribute to the observed dynamics.

4.4 Inferential Analysis and Interpretation

The study used yearly data to follow the same logic applied to the descriptive analysis. The next focus was the study of time periods, deal frequency and transaction amount, and their association with the dependent variable (brokerage). The measure of the association was carried out by conducting Chi-square tests. The author performed the Chi-square test yearly and presented an outcome based on the null hypothesis with a 5% significance level against the observed p-value. A decision and conclusion for each year and each test are presented. Results are consistent across all 10 years; for uniformity, the same years as the descriptive analysis, namely 2013, 2015, 2019, 2020 and 2022, are displayed. A different approach to transaction value was taken, where the entire 10-year period in a crosstabulation was analysed, and a Chi-square result was produced for the entire period. The model's reliability was tested by determining Cronbach's alpha and scaling all variables. A final section summary follows at the end.

Table 3.1: Guidance on Chi-square tables: presentation and interpretation

Statistic	Description
Pearson Chi-square	Measures the discrepancy between observed and expected frequencies. The higher the Chi-square value, the higher the discrepancies.
Degrees of Freedom	The number of categories in the variables analysed determines this.
Asymptotic Significance (2-sided)	The p-value was obtained from the Chi-square test. A value smaller than the significance level of 5% suggests a significant association between the variables being tested.
Likelihood Ratio	An alternative Chi-square test method is the linear-by-linear association (significant linear association tested).

Statistic	Description
	p-values lower than a 5% significance level suggest an association between the variables.
No. of valid cases	Indicates the number of valid cases in a year with no missing values.
Term ‘binned’	Used below when groups are created, which helps simplify and makes interpreting the vast dataset easier.
Chi-Square model	See Equation 1.

4.4.1 Time Periods in Years = First Year 2013

4.4.1.1 Time periods in years vs Brokerage

Table 3.2 summarises the Chi-square result achieved when testing the association between the yearly period 2013 and the brokerage charged.

Table 3.2: Summary of time periods vs brokerage results for 2013

Hypothesis	**Description**
Null hypothesis (H0)	There was no association between time periods in years and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between time periods in years and brokerage.
Level of significance	0.05
Observed p-value	Indeterminate (see Table 3.2.1).
Observation	The observed p-value was not determined because of the nature of the data.
Decision	No decision could be drawn since the p-value was not determined.
Conclusion	No conclusion could be drawn because the data could not be analysed.

Table 3.2.1: Chi-square test in 2013 for time periods vs brokerage

Chi-Square Tests	
	Value
Pearson Chi-Square	.[b]
No. of Valid Cases	33400

No time periods are computed because time periods in year b are constant.

4.4.1.2 Frequency (total trades per complete deal) vs Brokerage 2013

In 2013, a Chi-square test for association was performed to examine the relationship between deal frequency and brokerage. A crosstabulation was constructed, summarising the number of executions required to complete a single trade within different brokerage intervals. The findings indicated a significant association, with deal frequency exerting an influence on brokerage outcomes.

Table 3.3: Summary of frequency vs brokerage results for 2013

Hypothesis	Description
Null hypothesis (H0)	There was no association between the frequency of total trades per complete deal and the brokerage amount.
Alternative hypothesis (H1)	At least some significant association existed between the frequency of total trades per complete deal and brokerage.
Level of significance	0.05
Observed p-value	0.000 (See Table 3.3.1)
Observation	The observed p-value was smaller than the level of significance.
Decision	Since the p-value was far smaller than the significance level, the null hypothesis was rejected in favour of the alternative hypothesis.
Conclusion	The frequency of total trades per complete deal influences the brokerage amount.

Table 3.3.1: Chi-square test 2013 for frequency vs brokerage

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6135.597[b]	8	.000
Likelihood Ratio	5512.595	8	.000
Linear-by-Linear Association	5022.937	1	.000
No. of Valid Cases	33400		

Table 3.3.2: Crosstabulation in 2013 for time periods vs brokerage

		Brokerage (Binned) – Crosstab					
		<= 7000	7001 – 8206	8207 – 14980	14981 – 33600	33601+	Total
Frequency (total trades per complete deal) (Binned)	<= 1	12369	1329	4800	3857	1999	24354
	1 - 2	1424	258	1098	1474	1222	5476
	3+	375	92	392	902	1809	3570
Total		14168	1679	6290	6233	5030	33400

Time periods in years = First year 2013

Figure 4.6.1 clearly depicts where the frequency is dispersed across the various brokerage intervals. As concluded, the frequency of trades in 2013 influenced the brokerage amount.

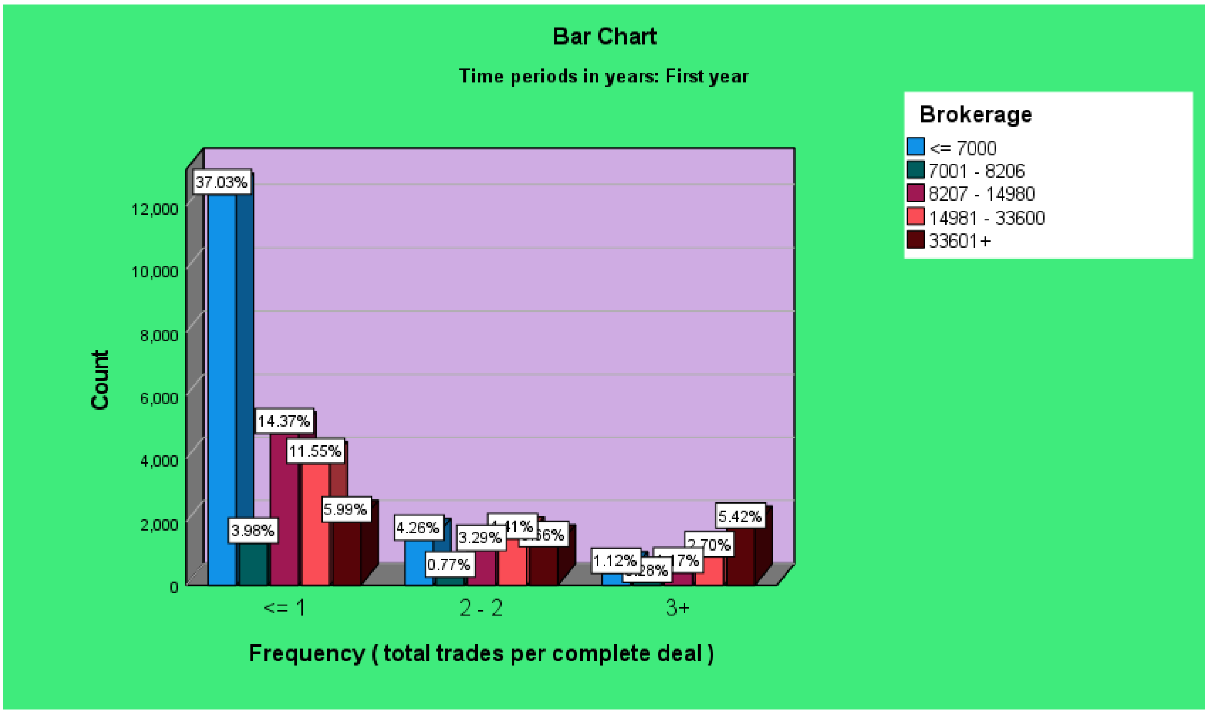


Figure 4.6.1: Frequency of deals in 2013

4.4.2 Time Periods in Years = Third Year 2015

4.4.2.1 Time periods in years vs Brokerage in 2015

The Chi-square result achieved when testing the association between the yearly period 2015 and the brokerage charged (hypothesis 1) is summarised in Table 3.4 The P-value is indeterminate at a 0.05 level of significance. This could be due to the volatile data in this study. Therefore, no decision and no conclusion could be drawn from the result.

Table 3.4: Summary of results in 2015 of time periods vs brokerage

Statistic	Description
Null hypothesis	H0: There was no association between time periods in years and brokerage.
Alternative hypothesis	H1: At least some significant association existed between time periods in years and brokerage.
Level of significance	0.05
Observed p-value	Indeterminate (See Table 3.4.1)
Observation	The observed p-value was not determined because of the nature of the data.
Decision	No decision could be drawn since the p-value was not determined.
Conclusion	No conclusion could be drawn because the data could not allow.

Table 3.4.1: Chi-square test in 2015 for time periods vs brokerage

Chi-Square Tests	
	Value
Pearson Chi-Square	.[b]
No. of Valid Cases	33400

No time periods are computed because time periods in year b are constant.

4.4.2.2. Frequency (total trades per complete deal) vs Brokerage in 2015

Table 3.4.2 summarises the Chi-square test for the association between the frequency of deals to complete a trade against brokerage in 2015. The author created a crosstab to count the executions for one, two, and three or more transactions to complete a single deal in each brokerage interval in 2015. A more explicit depiction is displayed in Figure 4.7.1. The null hypothesis is stated, followed by the outcome.

Table 3.4.2: Summary of results in 2015 for frequency vs brokerage

Hypothesis	**Description**
Null hypothesis (H0)	There was no association between the frequency of total trades per complete deal and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between the frequency of total trades per complete deal and brokerage.
Level of significance	0.05
Observed p-value	0.000 (See Table 3.4.3)
Observation	The observed p-value was smaller than the level of significance.
Decision	Since the p-value was far smaller than the significance level, the null hypothesis was rejected in favour of the alternative hypothesis.
Conclusion	The frequency of total trades per complete deal influences brokerage amounts.

Table 3.4.3: Chi-Square test 2015 for frequency vs brokerage

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6306.332[b]	8	.000
Likelihood Ratio	5668.391	8	.000
Linear-by-Linear Association	5281.478	1	.000
No. of Valid Cases	33400		

Time periods in years = Third year 2015

Figure 4.7.1 depicts that most trades took place with one deal completing the transaction, and 12807 of these trades had a brokerage rate lower than 7000 in value. Transactions taking two deals to complete the deal had an even spread across all brokerage intervals. The last category, where the frequency was three or more, had the most significant count of 2107 transactions within the brokerage interval of 33601 or more. The 2015 period shows a greater reliance on three or more deals to complete higher-value brokerages and an extremely high count for brokerage deals below 7000.

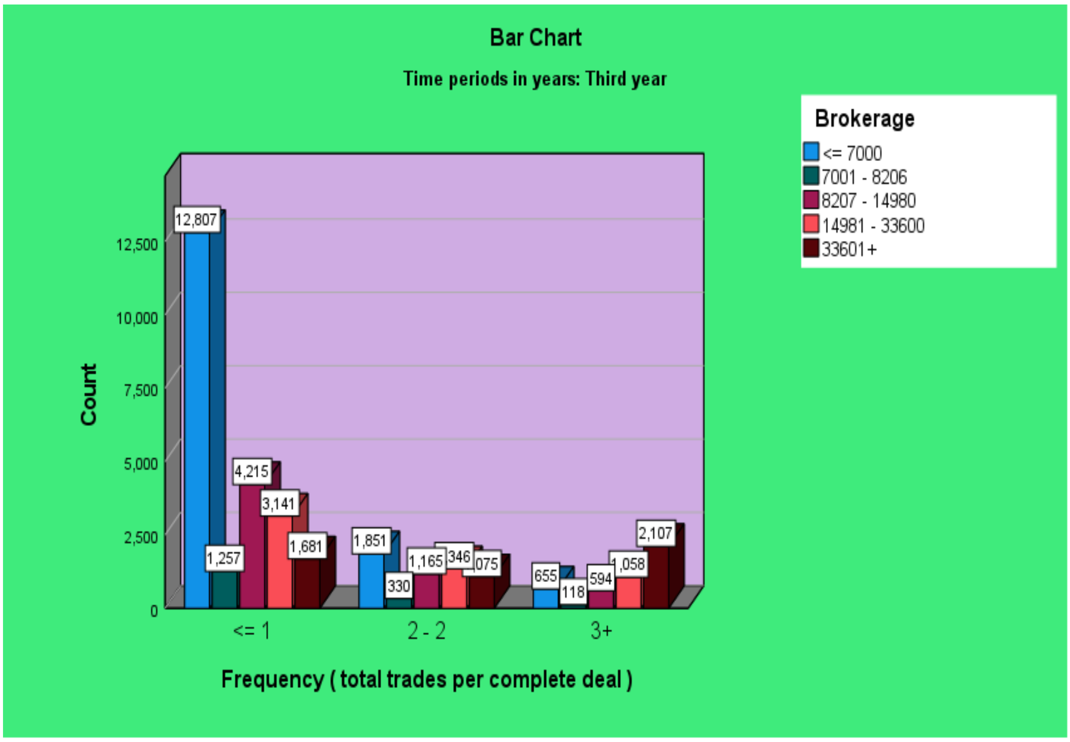


Figure 4.7.1: Frequency of deals in 2015

4.4.3 Time Periods in Years = Seventh Year 2019

4.4.3.1 Time periods in years vs brokerage 2019

A summary of the Chi-square result is displayed in Table 3.5, which was achieved when testing the association between the yearly period 2019 and the brokerage charged.

Table 3.5: Summary of results in 2019 for time periods vs brokerage

Hypothesis	**Description**
Null hypothesis (H0)	There was no association between time periods in years and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between time periods in years and brokerage.
Level of significance	0.05
Observed p-value	Indeterminate (See Table 3.5.1)
Observation	The observed p-value was not determined because of the nature of the data.
Decision	No decision could be drawn since the p-value was not determined.
Conclusion	No conclusion could be drawn because the data could not be analysed.

Table 3.5.1: Crosstabulation in 2019 for time periods vs brokerage

Count		**Brokerage – crosstab**					Total
		<= 7000	7001 – 8206	8207 – 14980	14981 – 33600	33601+	
Time periods in years B	Seventh year	16175	1226	4612	4967	5819	32799
Total		16175	1226	4612	4967	5819	32799

Table 3.5.2: Chi-square test for time periods and brokerage in 2019

Chi-Square Tests	
	Value
Pearson Chi-Square	.[b]
No. of Valid Cases	32799

No time periods are computed because time periods in year b are constant.

4.4.3.2 Frequency (total trades per complete deal) vs brokerage 2019

The Chi-square test for association between the frequency of deals to complete a trade against brokerage in 2019 is summarised in Table 3.5.3 The author created a crosstab to count the executions for one, two and three or more trades to complete a single deal in each of the brokerage intervals for 2019.

Table 3.5.3: Summary of results for 2019 of frequency vs brokerage

Hypothesis	Description
Null hypothesis (H0)	There was no association between the frequency of total trades per complete deal and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between the frequency of total trades per complete deal and brokerage.
Level of significance	0.05
Observed p-value	0.000 (See Table 3.5.4)
Observation	The observed p-value was smaller than the level of significance.

Hypothesis	Description
Decision	The null hypothesis was rejected since the p-value was smaller than the significance level.
Conclusion	It was concluded that the frequency of total trades per complete deal significantly influenced brokerage.

Table 3.5.4: Chi-square test in 2019 of frequency vs brokerage

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	9514.504[b]	8	.000
Likelihood Ratio	9085.532	8	.000
Linear-by-Linear Association	8425.075	1	.000
No. of Valid Cases	32799		

Table 3.5.5 is a crosstab showing the largest count of 13543 occurring for brokerage less than 7000 with a frequency of one trade to complete the deal. The opposite end of the crosstab sees the most considerable brokerage interval, 33601 or more, observing 3223 trades, with a frequency of three or more trades to complete the deal – a very similar picture to the 2015 outcome.

Table 3.5.5: Crosstabulation in 2019 of frequency vs brokerage

Count		Brokerage – crosstab					Total
		<= 7000	7001 – 8206	8207 – 14980	14981 – 33600	33601+	
Frequency (total trades per complete deal)	<= 1	13543	868	3032	2382	1410	21235
	1 – 2	1895	243	950	1292	1181	5561
	3+	737	115	630	1293	3228	6003
Total		16175	1226	4612	4967	5819	32799

4.4.4 Time Periods in Years = Eighth Year 2020

4.4.4.1 Time periods in years vs brokerage 2020

Table 3.6 summarises the Chi-square result achieved when testing the association between the yearly period 2020 and the brokerage charged.

Table 3.6: Summary of results for 2020 of time periods vs brokerage

Hypothesis	Description
Null hypothesis (H0)	There was no association between time periods in years and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between time periods in years and brokerage.
Level of significance	0.05
Observed p-value	Indeterminate (See Table 3.6.1)
Observation	The observed p-value was not determined because of the nature of the data.

Hypothesis	**Description**
Decision	Since the p-value was not specified, no decision could be drawn.
Conclusion	No conclusion could be drawn because the data could not be analysed.

Table 3.6.1: Chi-square in 2020 for time periods vs brokerage

Chi-Square Tests	
	Value
Pearson Chi-Square	. [b]
No. of Valid Cases	33401

No time periods are computed because time periods in year b are constant.

Table 3.6.2: Crosstabulation in 2020 of time periods vs brokerage

		Brokerage					Total
		<= 7000	7001 – 8206	8207 – 14980	14981 – 33600	33601+	
Time periods in years B	Eighth year	15816	1382	4746	5374	6083	33401
Total		15816	1382	4746	5374	6083	33401

4.4.4.2 Frequency (total trades per complete deal) vs brokerage 2020

The Chi-square test for association summary is displayed in Table 3.6.3, which shows the frequency of deals to complete a trade against brokerage in 2020. Figure 4.8.1 depicts a bar chart for clarity.

Table 3.6.3: Summary of results for 2020 of frequency vs brokerage

Hypothesis	**Description**
Null hypothesis (H0)	There was no association between frequency (total trades per complete deal) and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between frequency (total trades per complete deal) and brokerage.
Level of significance	0.05
Observed p-value	0.00 (See Table 3.6.4)
Observation	The observed p-value was smaller than the level of significance.
Decision	The null hypothesis was rejected since the p-value was smaller than the significance level.
Conclusion	It was concluded that the frequency of total trades per complete deal significantly influenced brokerage.

Table 3.6.4: Chi-square in 2020 of frequency vs brokerage

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	9005.359[b]	8	.000
Likelihood Ratio	8512.837	8	.000
Linear-by-Linear Association	7838.622	1	.000
No. of Valid Cases	33401		

Figure 4.8.1 shows the most significant occurrence on brokerage below 7000, with 39.88% of all deals occurring with one trade. The next largest occurrence occurs on brokerage between 8207 and 14980, with one trade to complete the deal 9.44% of the time. The third largest occurrence, 9.34%, occurred with three or more deals to complete the transactions with a brokerage of more than 33601.

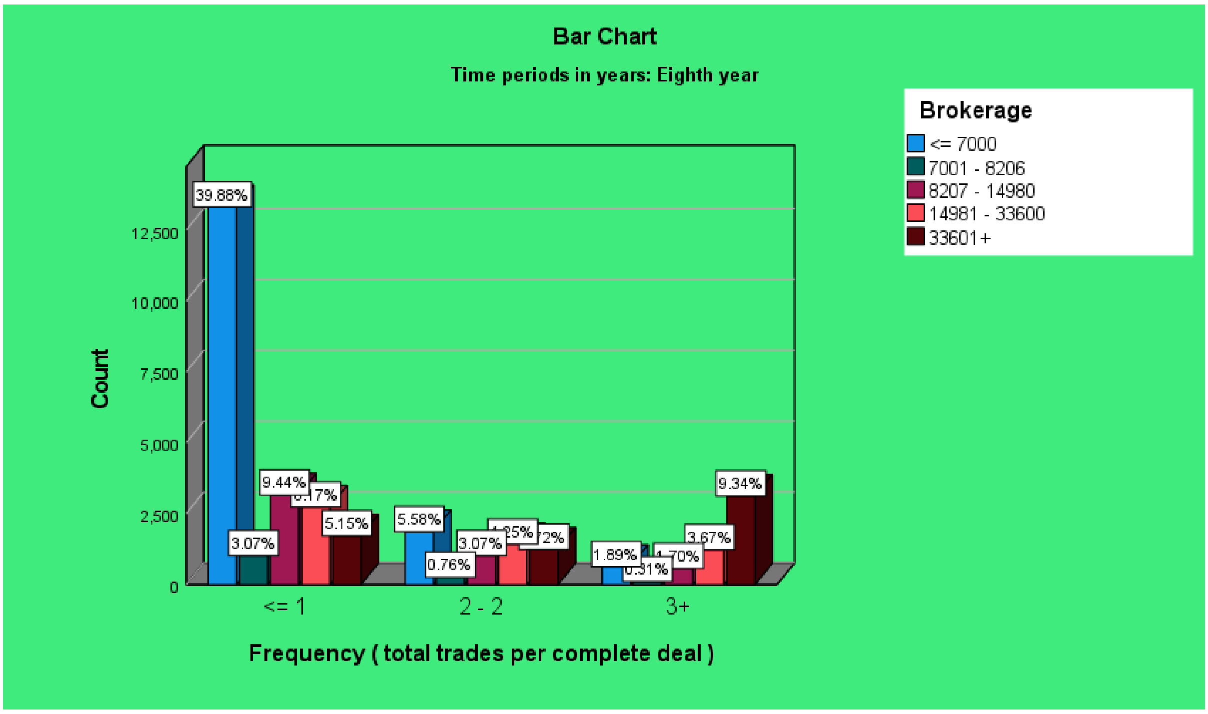


Figure 4.8.1: Chart in 2020 of frequency vs brokerage

4.4.5 Time Periods in Years = Tenth Year 2022

4.4.5.1 Time periods in years vs brokerage 2022

Table 3.7 summarises the Chi-square result achieved when testing the association between the yearly period 2022 and the brokerage charged.

Table 3.7: Summary of results in 2022 of time period vs brokerage

Hypothesis	**Description**
Null hypothesis (H0)	There was no association between time periods in years and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between time periods in years and brokerage.
Level of significance	0.05
Observed p-value	Indeterminate (See Table 3.7.1)
Observation	The observed p-value was not determined because of the nature of the data.
Decision	No decision could be drawn since the p-value was not determined.
Conclusion	No conclusion could be drawn because the data could not be analysed.

Table 3.7.1: Chi-square in 2022 of time periods vs brokerage

Chi-Square Tests	
	Value
Pearson Chi-Square	. b
No. of Valid Cases	33400

No time periods are computed, as time periods in year b are constant.

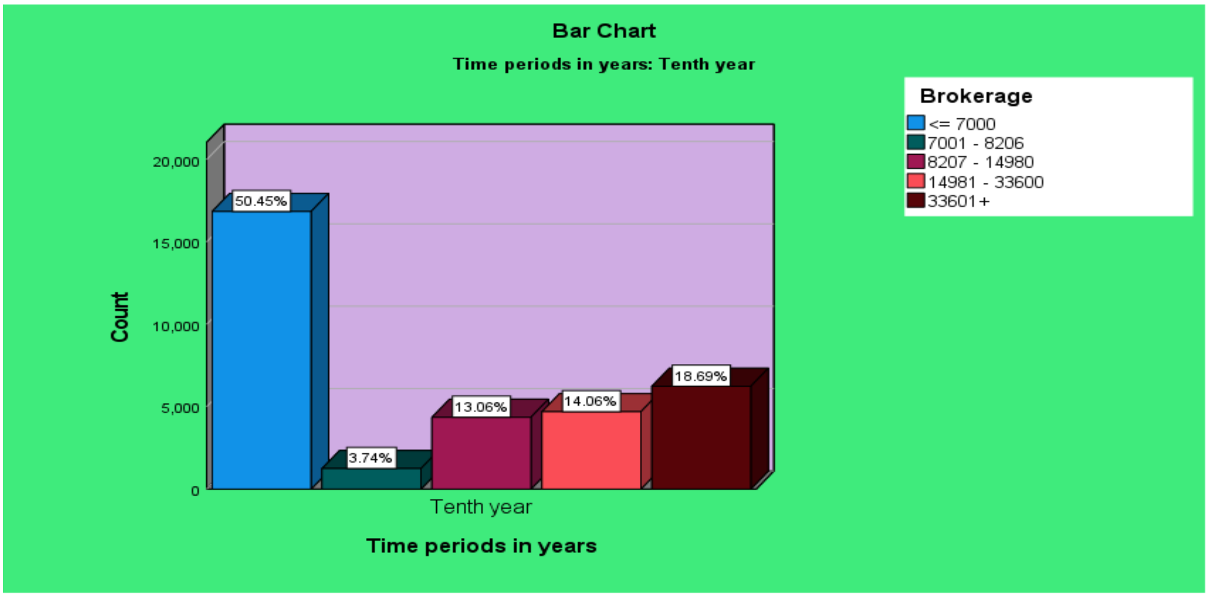


Figure 4.9.1: Chart of time periods in 2022

The bar chart in Figure 4.9.1 shows the dominance of brokerage values of less than 7000 during 2022, a common scene among all 10 years analysed.

4.4.5.2 Frequency (total trades per complete deal) vs brokerage 2022

Table 3.7.2 summarises the Chi-square test for association between the frequency of deals to complete a trade against brokerage in 2022. The author created a crosstab to count the number of executions for one, two, and three or more trades to complete a single deal in each of the brokerage intervals for 2022.

Table 3.7.2: Summary of results in 2022 for frequency vs brokerage

Hypothesis	**Description**
Null hypothesis (H0)	There was no association between frequency (total trades per complete deal) and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between frequency (total trades per complete deal) and brokerage.
Level of significance	0.05
Observed p-value	0.000 (See Table 3.7.3)
Observation	The observed p-value was far smaller than the level of significance.
Decision	The null hypothesis was rejected since the p-value was smaller than the significance level.
Conclusion	It was concluded that frequency (total trades per complete deal) influenced brokerage amounts.

Table 3.7.3: Chi-square in 2022 of frequency vs brokerage

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	9660.789[b]	8	.000
Likelihood Ratio	9163.080	8	.000
Linear-by-Linear Association	8530.546	1	.000
No. of Valid Cases	33400		

Table 3.7.4: Crosstabulation in 2022 of frequency vs brokerage

		Frequency vs Brokerage crosstab					Total
		<= 7000	7001 – 8206	8207 – 14980	14981 – 33600	33601+	
Frequency (total trades per complete deal)	<= 1	14269	924	2995	2362	1630	22180
	1 – 2	1863	238	888	1210	1384	5583
	3+	717	87	479	1124	3230	5637
Total		16849	1249	4362	4696	6244	33400

The crosstab in Table 3.7.4 again displays an analysis similar to previous years of study. Most observations occur with a frequency of one and a brokerage below 7000. There is an equal distribution for brokerage intervals of 7001 – 8206, 8207 – 14980, and 14981 – 33600 for a frequency of two or more deals. The same outlier would be for a brokerage of more than 33601, with 3230 being the second most counted in 2022.

4.4.6 Transaction Value vs Brokerage 2013–2022 (Full Yearly Periods)

Table 3.8 summarises the Chi-square test for association between the transaction value traded against brokerage over the entire analysis period. The author created a crosstab to count the executions for each transaction value interval against each brokerage interval for the whole of the analysis period, i.e., 2013 through 2022.

Table 3.8: Summary of results 2013 to 2022 for transaction value vs brokerage

Hypothesis	**Description**
Null hypothesis (H0)	There was no association between transaction value and brokerage.
Alternative hypothesis (H1)	At least some significant association existed between transaction value and brokerage.
Level of significance	0.05
Observed p-value	0.000 (See Table 3.8.1)
Observation	The observed p-value was far smaller than the level of significance.
Decision	The null hypothesis was rejected since the p-value was smaller than the significance level.
Conclusion	It was concluded that transaction value influenced brokerage amounts over the entire analysis period with full yearly periods.

Table 3.8.1: Chi-square of transaction value vs brokerage over the entire period

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	519985.265[a]	24	.000
Likelihood Ratio	510386.173	24	.000
Linear-by-Linear Association	257433.829	1	.000
No. of Valid Cases	333999		

Table 3.8.2: Crosstabulation of transaction value vs brokerage

Transaction amount vs Brokerage amount Crosstabulation							
Count							
		Brokerage amount					Total
		<= 7000	7001 – 8206	8207 – 14980	14981 – 33600	33601+	
Transaction amount	<= 2043.96	46150	17	1478	82	2	47729
	2043.96 – 5306.85	44584	21	3026	85	9	47725
	5306.85 – 10154.49	43223	1264	3150	88	1	47726
	10154.49 – 18098.21	12362	10381	24829	147	20	47739
	18098.21 – 32198.73	6050	2687	16730	22201	66	47734
	32198.73 – 76163.07	50	213	6480	26500	14486	47729
	76163.07+	30	0	0	6613	40974	47617
Total		152449	14583	55693	55716	55558	333999

The crosstab in Table 3.8.2 further elaborates and shows the relationship determined by the Chi-square results, showing a significant association between transaction value and brokerage over the entire period. There was a large concentration at either end of the distribution, most densely recorded in the lower transaction value intervals with brokerage amounts lower than and equal to 7000 with a count of 152449. On the opposite side, the author witnessed less observations (55716 and 55558) in the 14981 – 33600 and the 33601+ brokerage intervals. The higher transaction amount intervals, 32198.73 – 76163.07 and 76163.07 or more had the highest brokerage observations. The author observed lower transaction amounts influencing lower brokerage amounts and vice versa.

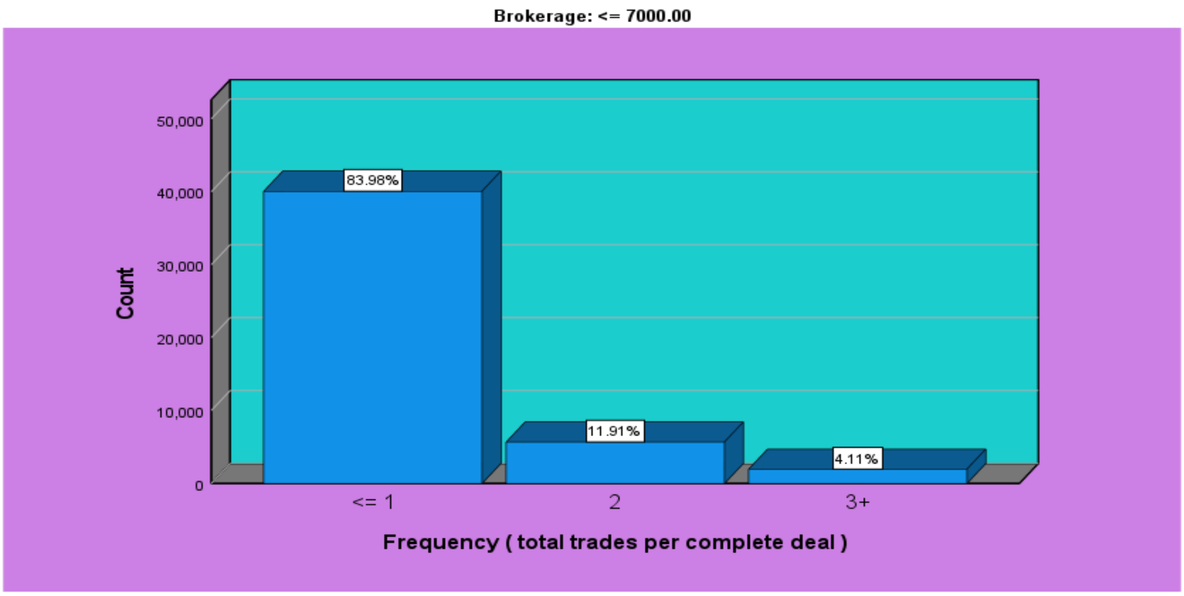


Figure 4.10.1: Brokerage <= 7000 over the period vs frequency

A graphical depiction in Figure 4.10.1 clearly shows how the lower-valued brokerage charges (<= 7000) are skewed towards only needing one deal to execute the entire trade, with 83.98% of trades taking place here. On the other end of the spectrum in Figure 4.11.1, the higher-valued brokerages of 33601 and more have a greater likelihood of needing three or more trades to complete the deal, with 49.84% of all deals falling here.

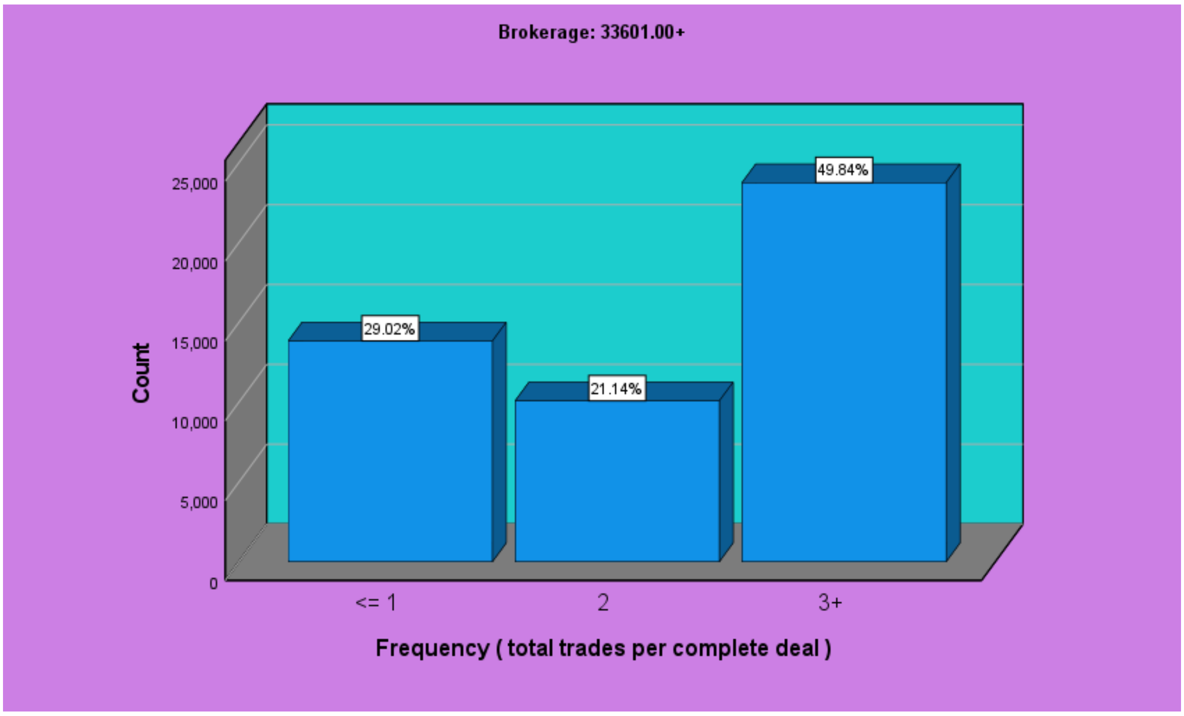


Figure 4.11.1: Brokerage of 33601+ over the period and frequency

4.4.6.1 Reliability

The author tested the reliability of the internal consistency of the scale of all variables by measuring the variables' Cronbach's Alpha, which assessed how closely variables were related from 0 to 1. The higher the values, the greater the reliability. A decrease in Cronbach's Alpha indicates an increase in the number of variables failing to measure the same concept consistently. Higher Alpha values suggest the scale is more reliable in measuring the same underlying construct. An acceptable level is 0.7 or above.

Table 4.1: Reliability tests for 2013 to 2022

Reliability Statistics	
Cronbach's Alpha	N of Items
.771	2

Item Statistics		
Mean	Std. Deviation	N
55323.5001	221781.42798	334000
27993.9231	83695.62115	334000

Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Absolute Tx amount	27993.9231	7004957000.495	.949	.
Brokerage	55323.5001	49187001795.986	.949	.

The Cronbach's Alpha of 0.771 in Table 4.1 suggests moderate reliability and consistency between the absolute transaction value and brokerage. The author observed a significantly correlated relationship between absolute transaction value and brokerage at 0.949. A corrected item-total correlation of 0.949 shows a strong positive correlation, indicating greater item consistency, and removing either could impact the scale's reliability. When items were excluded, the mean and variance were consistent, which suggested that items were well aligned with the overall scale and contributed to its measurement.

The relationships between the transaction amount, frequency and brokerage are related to the findings in the literature; for instance, according to Ingrassia (2021), new technologies have made online trading more accessible for younger investors, democratising and revolutionising private retail investing and changing its ecosystem. The findings of this research are in line with Ingrassia (2021), who agrees that this could be a driver for the smaller brokerage of 7000 cents being the dominant interval. The transparency in trading online allows online retail investing clients to execute most of their deals in one trade.

When determining the price structure of platforms, three factors come into play. These include the relative size of cross-group externalities, the type of model used (subscription or payment-per-transaction), and whether or not the customer uses multiple platforms to complete the desired activity (Rohn et al., 2021). The author believes all trades can be executed through this single platform through a monthly subscription price.

According to Croxson et al. (2021), banks that operate on platforms earn about 40% of their revenue from fees and non-interest income. This is a significant shift from the past, where interest income was the primary source of banking revenue. In contrast, traditional banks only generate about 33% of their revenue from fees and non-interest income. The author aims to replace most future revenue by offering a fixed monthly fee that covers the most common brokerage intervals, transaction values and frequencies, similar to a flat monthly fee. These revenue model shifts do occur, as pointed out by Croxson et al. (2021), and a change is needed for the model to closely align with frequency, transaction value and brokerage associations observed above.

4.4.6.2 Summary of Inferential Analysis

The results unanimously showed no relationship between yearly time periods and the brokerage. This was the result for all 10 years analysed and demonstrated in 2013, 2015, 2019, 2020 and 2022. The hypothesis results for time periods and brokerages show no relationship, which supports the null hypothesis.

When analysing frequency (deals per trade) and its relationship with brokerage variable, all 10 years showed an association between the two variables. Therefore, the null hypothesis that there is no relationship between frequency and brokerage can be rejected.

The author analysed the transaction value and its relationship with brokerage from 2013 to 2022, where clear association was observed between the two variables in the Chi-square testing. Therefore, the null hypothesis that there is no relationship between transaction value and brokerage amounts can be rejected, as there is a relationship.

The first research question was: ‘What are the effects of time periods, trading frequency, and transaction value on brokerage rates?’ This question has been answered, and Null Hypothesis 1, which stated that there is no relationship between time periods, trading frequency, transaction value, and their effect on brokerage rates, was rejected for both trading frequency and transaction values. This proves that a relationship does indeed exist between these factors and brokerage rates.

Next, the author used brokerage regression modelling with time-series data to determine a fixed subscription price. The analysis used transaction value and frequency variables, which had significant relationships.

4.5 Brokerage Regression Modelling with Time-Series Data

4.5.1 Introduction

This section presents the modelling result, including estimates and analysis of the approach to predicting the brokerage's daily fixed fee value. Furthermore, interpretations of the results that support the selected regression model are presented here.

The process started with importing data and preparation, visualisation through boxplots, and statistical testing through KPSS. The time-series' autocorrelation and partial autocorrelation functions were presented, and then the model was fitted to the prepared time-series data. The last two steps compared linear predictions to actual data, then calculated the residual sum of squares for the fitted models. The R code used to obtain all the discussed results can be found in the appendices labelled Appendix B: R-code section B.

4.5.2 Time-Series Analysis

First, Table 5.1 presents the initial descriptive statistics for the dependent and independent variables that address the empirical specification in Equation 3.

$dl\_chg\_bro_t = \alpha + B_1 dl\_Absolute\_Tx\_amount_t + B_2 d\_del\_seq_t +$
$B_3 dl\_abs\_trans\_x\_d\_del\_seq_t + \Upsilon x_t + e_t$...**Equation 3**

Where dl_chg_bro is brokerage amount value in cents, $dl\_Absolute\_Tx\_amount\_t$ is absolute transaction amounts in Rands, d_del_seq is frequency of transactions, $dl\_abs\_trans\_x\_d\_del\_se$ is the interaction between transaction amount and frequency of transactions, x_t are other controls such as seasonality and e is the error term.

From Table 5.1, on average, brokerage, transaction amount and transaction frequency are observed as 27 718, 54 889 and 1.86, respectively.

Table 5.2: Descriptive statistics

	del_seq	***chg_bro***	***Absolute Tx amount***
Mean	1.86	27,718	54,889
Standard Error	0.02	469	1,220
Median	1.85	26,470	52,587
Standard Deviation	0.20	5,325	13,915
Sample Variance	0.04	28,357,955	193,615,295
Range	1.12	31,133	77,316
Minimum	1.49	19,852	33,803
Maximum	2.61	50,984	111,119
Sum	239.85	3,575,659	7,135,530
Count	129.00	129	130
Largest (1)	2.61	50,984	111,119
Smallest (1)	1.49	19,852	33,803
Confidence Level (95.0%)	0.03	928	2,415

Furthermore, the median for the mentioned variables is very close to the mean (frequency mean of 1.86 and median of 1.85), which also gives some preliminary confidence that the underlying distribution for the target variable and the explanatory variables are normally distributed. The box plot shown in Figure 5.1 (d) corroborates this perspective, particularly evident in the frequency averages (represented by the orange block) that predominantly adhere to a normal distribution. At the same time, for brokerage (grey) and transaction amount (blue), the log of the values will need to be applied to reduce the high variance observed in the descriptive statistics in Table 5.1. The box plot shows the transformed values for the different variables all close together.

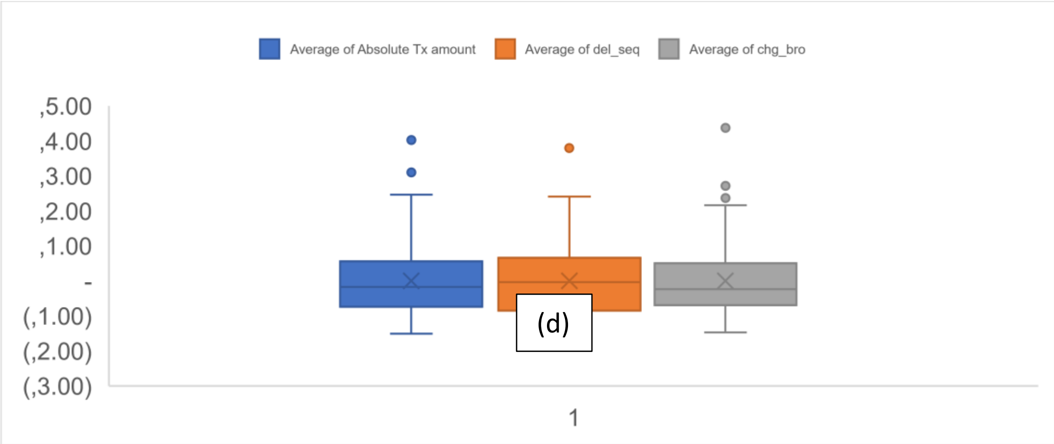


Figure 5.1: Variable relationships and outliers with averages

Petri (2014) proposed five critical dimensions in pricing, and focusing on the price formula metric, the author has adopted a fixed monthly price model with a limit of two trades per month. This pricing strategy aligns with the average frequency of 1.86 trades observed in the results and is positioned to the left of Petri's table, as shown in Chapter Two. The dynamics of two-sided platform markets are influenced by various factors, including the platform's structure, the frequency of user transactions, and the value of those transactions, rather than being determined solely by the fees charged by the platform (Rochet & Tirole, 2006). The author identified that in the brokerage data analysed, both frequency and transaction value influence the brokerage charge.

Appendix A shows the time-series analysis process flow that was followed, namely: step 1: identifying the components in the given dataset; step 2: the stationarity check; step 3: converting data into a stationary variable; and step 4: autocorrelations and partial autocorrelation functions, before the ARIMA auto-regression and moving averages are modelled. For a comprehensive analysis, it is essential to develop a prediction model using stationary data free from irregularities and encompassing all potential cycles that might affect the regression outcomes. Initially, these aspects are delineated and examined prior to the author conducting the time-series analysis in the subsequent section.

Table 5.2: KPSS Test

Variable	KPSS Trend	Lag order	p-value
Original (chg_bro)	0.75326	9	Less than 0.05
Differenced (chg_bro)	0.0027276	9	More than 0.05
Original (abs trans amount)	0.45928	9	Less than 0.05
Differenced (abs trans amount)	0.0018207	9	More than 0.05
Original (del_seq)	0.66512	9	Less than 0.05
Differenced (del_seq)	0.0052428	9	More than 0.05

Moreover, the KPSS stationary test in Table 5.2 shows that the observed p-values in their original form are less than the 5% significance level for all variables. This suggests that all three-time series are non-stationary, and there is a need to remove the upward trend seen on the original time-series plots in Figures 5.2 (a, b and c). The author differences the variables to change the scale of the variables, to ascertain if there is the same variance across stationary variables. The main aim is to establish stationarity; when p-values are significant, it suggests that there is no trend. Means and variances need to be constant for stationarity.

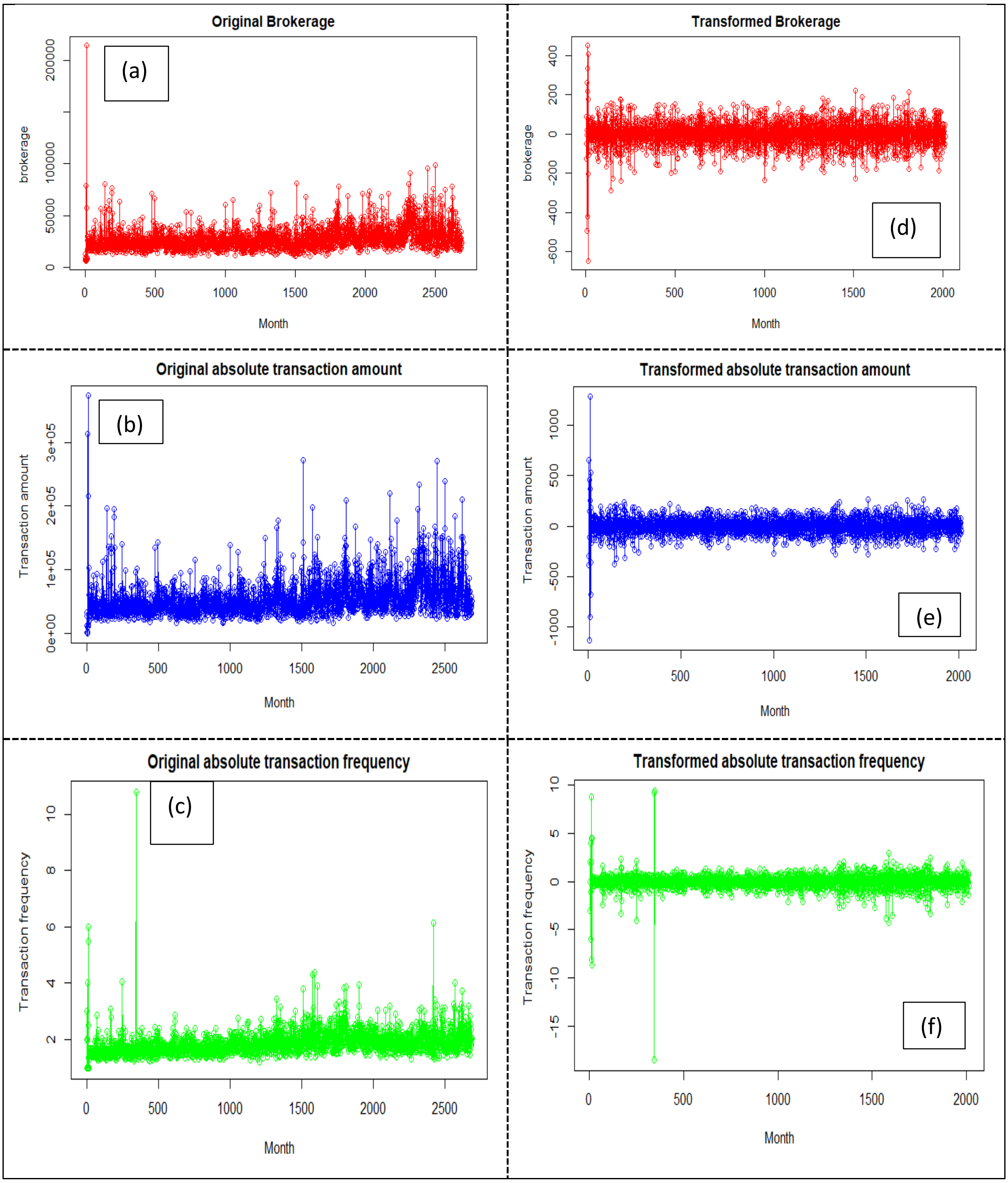


Figure 5.2: Original time series compared to differenced

Moreover, the autocorrelation function (ACF) graph displayed in Figure 5.3 (a, b and c) features a noticeable long tail that persists without quickly diminishing, indicating that not all trends are stationary.

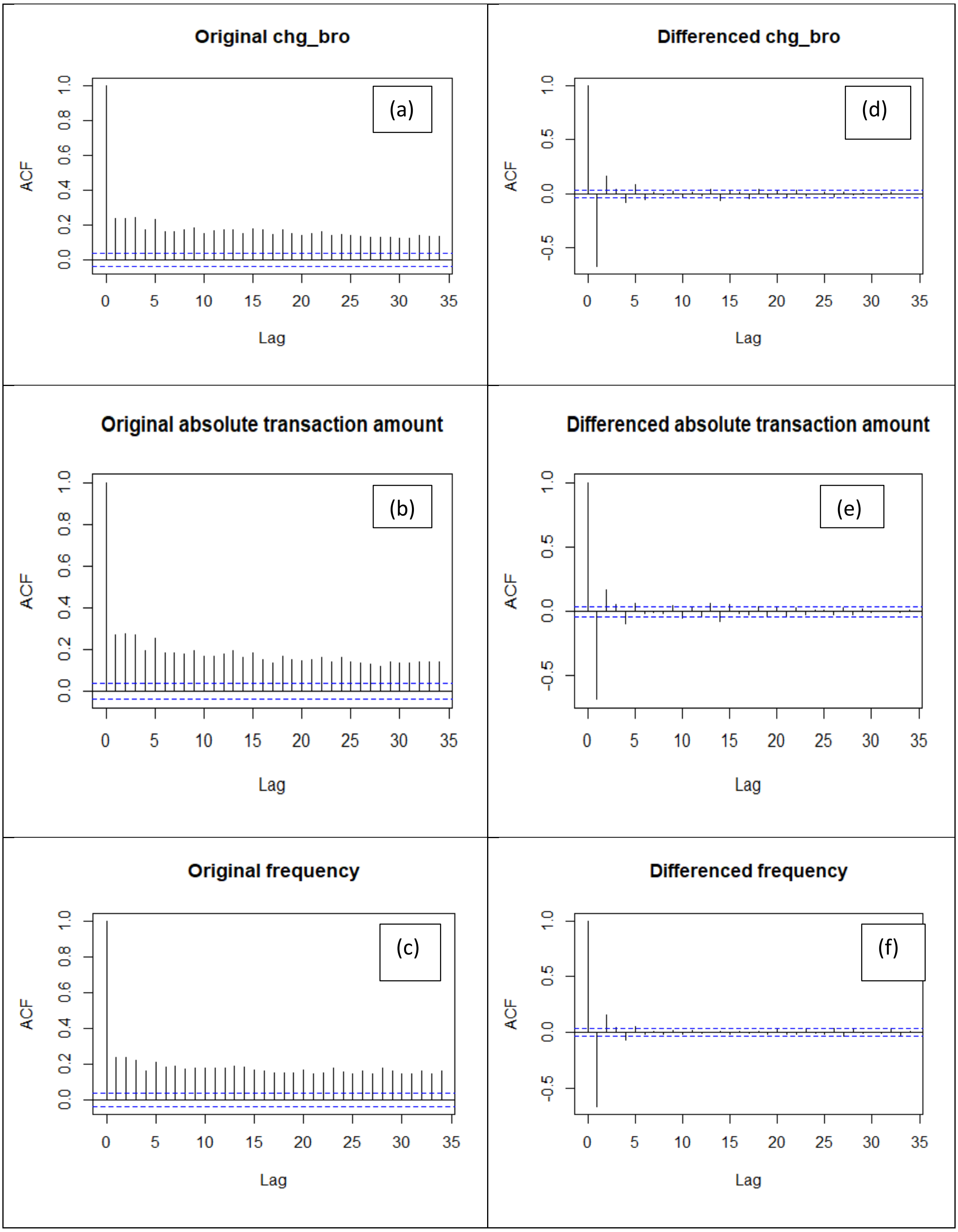


Figure 5.3: Autocorrelation function, original vs differenced

Hence, the brokerage and transaction amounts have been differenced twice and logged to achieve stationarity. At the same time, only two levels of differencing have been applied for frequency. The resulting stationary trends can be seen in Figure 5.2 (d, e and f), which are also justified by the KPSS test that shows that all p-values are greater than 5%, as well as the ACF graphs in Figures 5.3 (d, e and f) which now show that there is no long tail. The Dickey-Fuller test can be found in Appendix C, which also saw the original variables as non-stationary.

On the other hand, yearly, monthly and daily seasonality checks are all insignificant, as the distribution in the box and whisper for all the variables in Figure 5.4 are all the same for all years and months, with minimal variance.

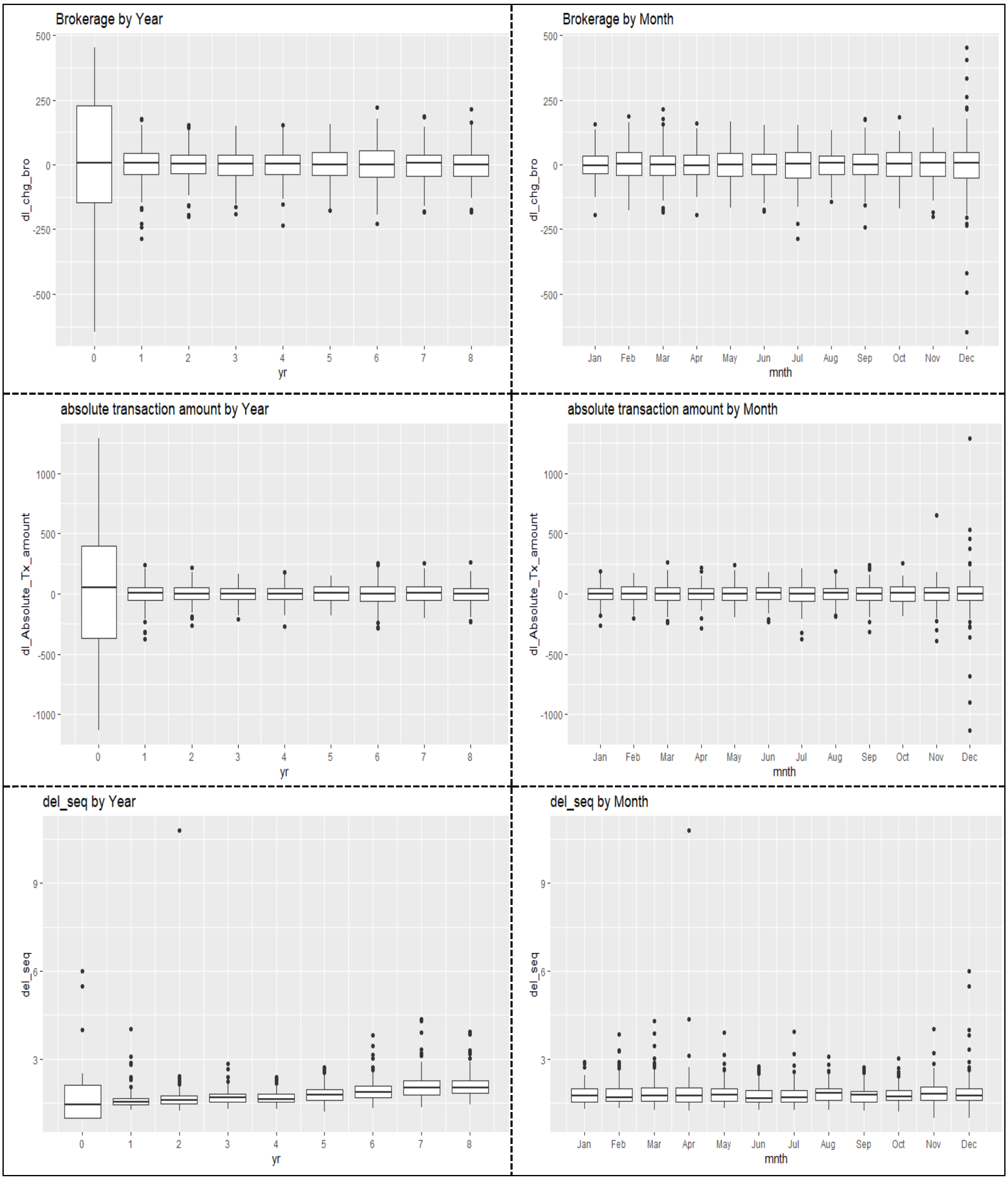


Figure 5.4: Yearly and monthly seasonality check

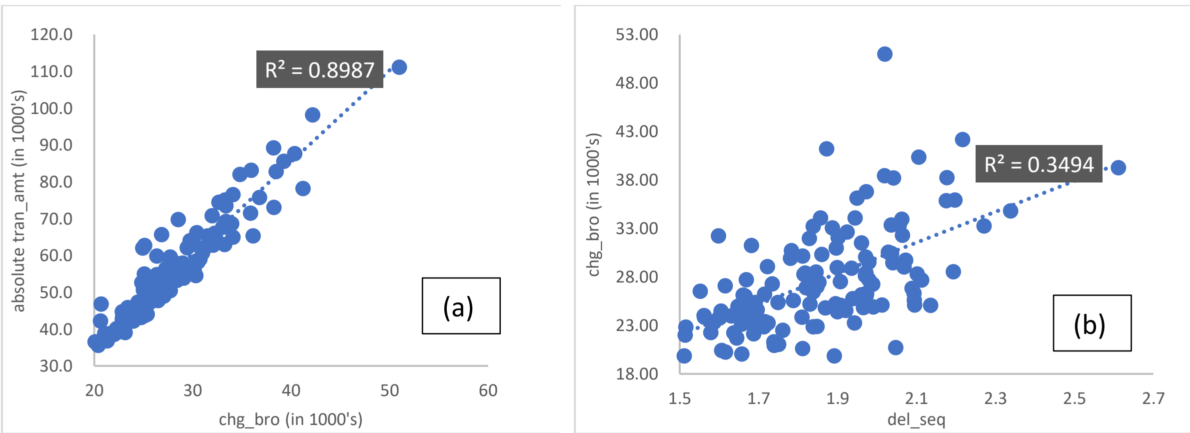
4.5.3 Time-Series Prediction

Based on the preliminary time-series descriptive analysis carried out and discussed in section 4.5.2 on the data to achieve stationarity, the linear regression model and the ARIMA model are the two models that have been considered for prediction. These models are supported by the model selection criteria in Table 5.3, favouring the moving average model, as the ACF (autocorrelation function) and PACF (partial autocorrelation function) plots show an instant drop and a gradual decline, respectively. Thus, the linear regression model has been used as the primary model, and the ARIMA has been included for comparison.

Table 5.3: Model selection criteria

ACF	PACF	Perfect ML-Model
Plot declines gradually	Plot drops instantly	Autoregressive model
Plot drops instantly	Plot declines gradually	Moving average model
Plot declines gradually	Plot declines gradually	ARMA
Plot drops instantly	Plot drops instantly	No possible model

In Figure 5.5 (a and b), it can be seen that the dependent variable is most correlated with the transaction amount at 0.8987, but least associated with the transaction frequency at 0.3495. Furthermore, as a check for multicollinearity, in Figure 5.5 (c), the link between the independent variables is examined, and the association level is at 0.4796. A positively correlated R-squared explains the relationship between independent and dependent variables.



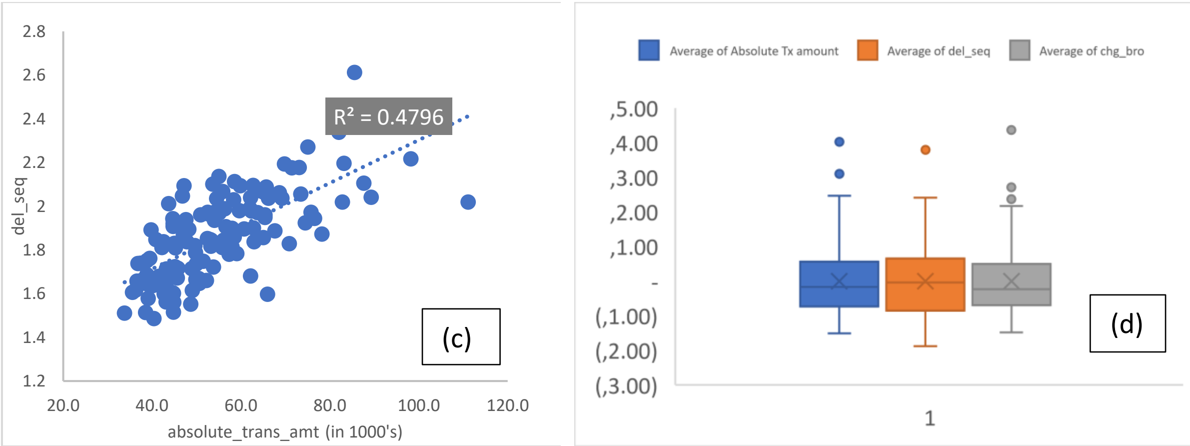


Figure 5.5: Variable relationships and outliers

Moving on to the prediction, causal estimates from the daily linear model also support the observed high correlation with any change in the absolute transaction amount or transaction frequency impacting brokerage. These changes increase the brokerage values and are significant at 0.1% with an 85.71% prediction power (see Table 5.4). The interaction between transaction amount and frequency leads to an inverse relationship between the two variables.

Table 5.4*:* Causal estimates for the linear model

Variable	Coefficient	S.E	Test Stat	P-Value
Intercept	0.31	2.33	0.13	0.893
Absolute transaction amount (logged)	0.68	0.01	107.80	< 2e-16 ***
Transaction frequency	2.81	0.65	4.30	1.74E-05 ***
Interaction between transaction amount and frequency	(0.01)	0.00	(5.35)	9.52E-08 ***
Weekday	(0.23)	0.37	(0.62)	0.533
Month	0.07	0.15	0.48	0.633
Year	0.00	0.17	0.00	0.996
Day	0.04	0.06	0.64	0.524

Residual standard error: 26.95 on 2 679 degrees of freedom. Multiple R-squared: 0.8571, Adjusted R-squared: 0.8568, F-statistic: 2296 on 7 and 2679 DF, p-value: < 2.2e-16.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The causal estimates in Table 5.4 provide an F-statistic of 2296, indicating that the linear regression model is statistically significant. Transaction frequency and absolute transaction amount appear highly significant again, as previously proven, with p-values less than 0.001. Furthermore, time periods are not statistically significant, with weekday, month, year and day period p-values all above 0.05.

The goodness of fit statistics in Table 5.5 favour linear regression, as the R-square is the highest for the linear model at 0.85, whereas the sum of squares is the lowest. This implies that high transaction amounts or an increased number of transactions associated with high brokerage bring about a high value at risk (VAR), which shows that transactions involving high amounts and/or high volumes of transactions require a higher value at risk. However, when the transaction amount and frequency are high, the brokerage value declines, and the VAR required to cover a broker is low. This means that the online stockbroker should attempt to attract more investors towards days or months when there are high transaction amounts coupled with a higher frequency of trades to lower the brokerage value-at-risk.

The author considered that attempting to attract trading to specific months or days can add undue pressure and market volatility. Nevertheless, it will increase participation and transparency in the long run. According to a recent study by Pagano et al. (2021), the participation of retail investors in financial markets can significantly affect trading quality, especially during times of market stress.

Table 5.5: Goodness of fit statistics

Model	R^2	**Sum of squares**
Linear regression	0.85	1 946 078
ARIMA	0.40	7 517 521

Figure 5.6 compares actual brokerage occurrences in black with predicted values from linear regression in red and the ARIMA-modelled prediction in green. This demonstrates graphically how the linear regression is more closely related to an R-squared of 0.85. The author displays the graph to illustrate how the linear model has a closer predictive ability than the ARIMA model. The author has used this predictive

ability to suggest a unique fixed monthly fee based on past daily variable brokerage charges.

Fixed fees such as membership or platform fees could be the most efficient way to capture end-user surplus; these fixed fees are in place to cover the platform costs (Rochet & Tirole, 2006). The author agrees that greater emphasis and reliance should be placed on a fixed fee as proposed instead of the variable transaction-based fees currently being used.

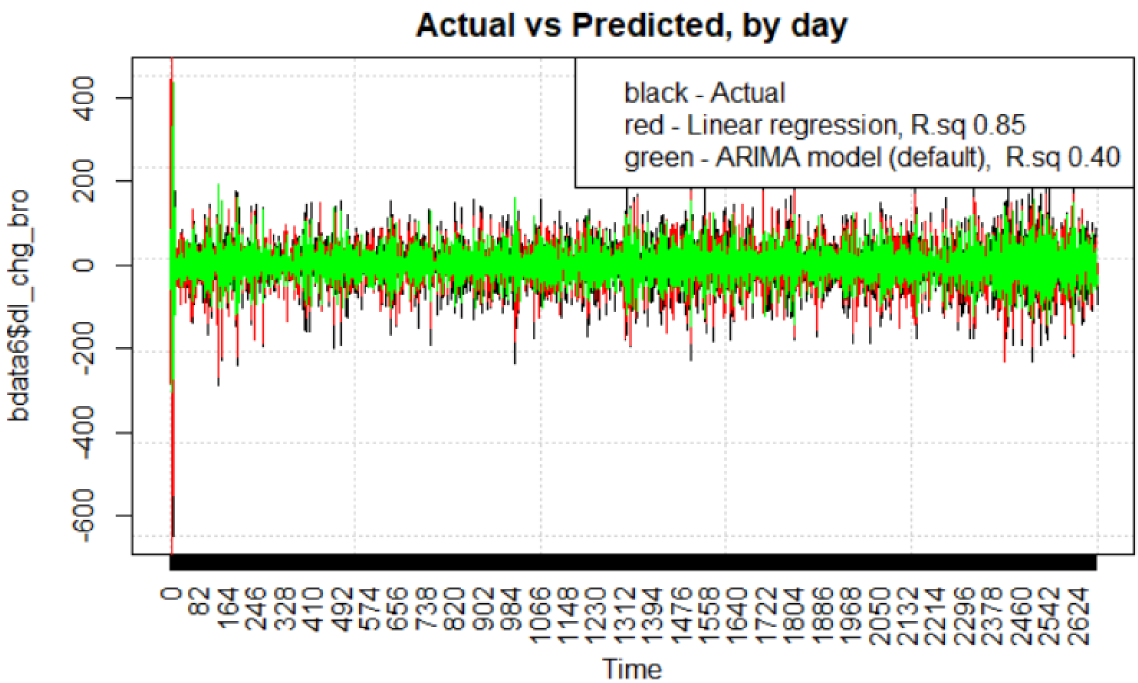


Figure 5.6: Linear regression and ARIMA predictions

Petri (2014) explains that the price model should be configured to ensure a steady influx of revenue while delivering long-term value to customers. The author models a fixed subscription-based price based on past variable rates, changing the revenue from variable to fixed to an annuity income. There are additional expectations that users will be attracted to this new pricing model, with the potential for network effects. Network effects are enhanced and exaggerated through frictionless entry and the ability to scale rapidly, maximising their value-building impact (Parker et al., 2016). In platform markets, attracting more users decreases the average cost per user and increases the average return. Users' willingness to join increases revenue (Croxson et al., 2021).

Lastly, the autocorrelation function (ACF) of the residuals in Figure 5.7 drops instantly, further justifying the 0.85 goodness of fit observed on the linear model. Nothing is left to be additionally modelled, as the author has completed all the planned steps.

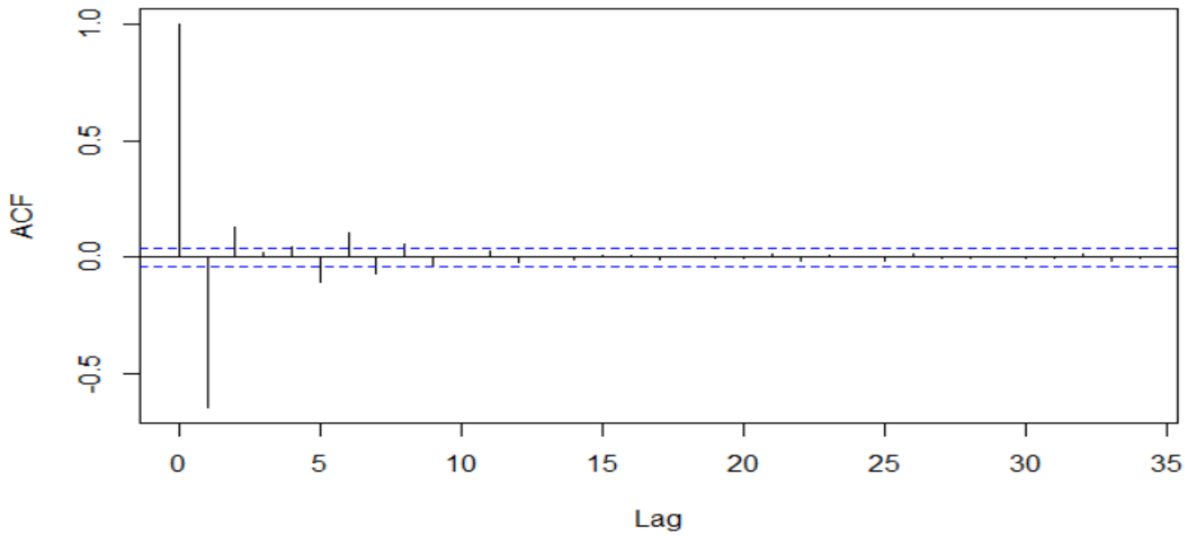


Figure 5.7: PLOT ACF for residuals of the ARIMA model, ensuring no more information is left for the linear model

The author has completed all steps to validate the linear model and can now use the various estimates found in Table 5.4 and the empirical specification explicitly built for this dataset to establish a fixed monthly subscription amount.

Steps the author has followed to predict a monthly fixed subscription fee:

1. Randomly selected eight client trades from the historic variable fees.
2. Created an interaction column = frequency x Absolute transaction amount.
3. From the order date specified which year: for example, 2013 = 1; month: February = 2; and the specific day.
4. Inserted the specific data for the trade along with the relevant coefficient into the empirical specification to obtain the predicted daily fixed fee.
5. The fixed brokerage prediction amount is in cents; the daily Rand amount obtained by dividing by 100.

6. This daily fixed fee prediction then multiplied by 20 (trading days in a month) to convert into a monthly fixed subscription fee.
7. The monthly Rand amount obtained by dividing the monthly prediction by 100; the monthly Rand amount represents the fixed monthly subscription amount.

The empirical specification: Equation 3

$$dl\_chg\_bro_t = \alpha + B_1 dl\_Absolute\_Tx\_amount_t + B_2 d\_del\_seq_t + B_3 dl\_abs\_trans\_x\_d\_del\_seq_t + \Upsilon x_t + e_t$$

To further illustrate the calculation, including the coefficients:

$$l_{chg_{bro_t}} = 0.311783 + 0.675134 * X_1 + 2.806 * X_2 - 0.01114 * X_3 - 0.2308 * X_4 + 0.07286 * X_5 + 0.000743 * X_6 + 0.037781 * X_6 + 26.95$$

Table 5.6: Random sample of data to show predictions of the model

acc_cde	Prediction	Difference	VaR adjustment	Daily Rand	Monthly Prediction	Monthly Rand Prediction
A	40544,12	-2519,879	decrease	R405,44	810882,42	R8 108,82
B	56115,73	-3496,265	decrease	R561,16	1122314,69	R11 223,15
C	5317,01	-1682,986	decrease	R53,17	106340,29	R1 063,40
D	6873,55	-257,455	decrease	R68,74	137470,90	R1 374,71
E	13137,89	-528,112	decrease	R131,38	262757,76	R2 627,58
F	13036,30	-1003,697	decrease	R130,36	260726,06	R2 607,26
G	16221,42	3718,422	Increase	R162,21	324428,45	R3 244,28
H	12288,48	-745,520	decrease	R122,88	245769,60	R2 457,70

Table 5.6 shows the prediction based on the empirical specification using historical data of random client trades through the 10 years. The difference is based on the historical brokerage paid versus the predicted daily brokerage in cents. The VAR adjustment shows an increase or decrease in the predicted brokerage amount against the actual paid, where the prediction is higher, hence there is a higher risk. The account code has been replaced with a letter for anonymity but remains consistent across further testing.

Figure 5.8 shows how close the daily brokerage prediction model is to the actual historic brokerage. The author found a daily prediction model to be more accurate and comparable to actual brokerage than converting the daily prediction to a monthly prediction model.

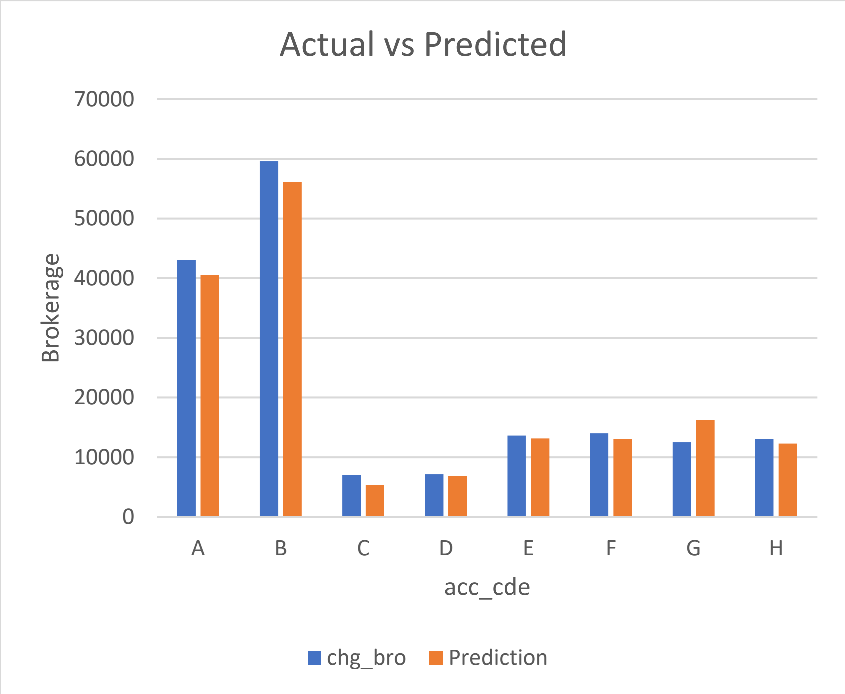


Figure 5.8: Daily actual brokerage vs predicted brokerage

Looking at the five critical dimensions of pricing proposed by Petri (2014) and zooming into the price formula metric, the author has approached the proposed revenue model by shifting entirely to the left of Petri's table and providing a fixed monthly price. The author's model demonstrates it can predict a fixed monthly fee to move to an annuity-type model in line with a global shift in top major banks and financial institutions worldwide. Platform-based banks now generate almost 40% of their revenue from fees and non-interest income, where previously this used to be dominated by interest income as the sole source of banking revenue, according to Croxson et al. (2021).

4.5.4 Summary of Time-Series Analysis

The author went through rigorous and meticulous steps to ensure the model chosen to predict future brokerage values is appropriate and correct. Data was imported, cleaned, visualised, and statistically tested while fitting models and comparing their performances of different modelling techniques.

The empirical specification was proven to predict Equation 3:

$$dl\_chg\_bro_t = \alpha + B_1 dl\_Absolute\_Tx\_amount_t + B_2 d\_del\_seq_t + B_3 dl\_abs\_trans\_x\_d\_del\_seq_t + \Upsilon x_t + e_t$$

The author began by identifying normality within the variables, subsequently detected non-stationarity, and then addressed these anomalies. The time-series prediction steps showed that a linear regression model was a better fit for the data, while the ARIMA model was used as a comparison. The goodness of fit favoured the linear regression model, where the independent variables explained 85% of the variance in the dependent variable brokerage, defining a more significant portion of the variance than the ARIMA model. Finally, the development of practical steps for employing the empirical model, including its application to historical data for the purpose of projecting a monthly fixed brokerage fee to attract clients, was elaborated.

Many authors suggest using a fixed subscription fee in platform models. This approach can work in online stockbroking, as a superior platform model will experience network effects leading to the growth required to scale appropriately. Equation 3 was utilised to determine a fixed monthly subscription price. This was done by analysing the same historic client brokerage data monthly. The goal was to ascertain if clients would opt for the new fixed monthly fee or not as part of addressing Hypothesis 2.

4.6 Modelling Customer Decision-Making between a Fixed or a Variable Brokerage Charge

The author first analysed the historical data over the same set of clients, A to H, chosen in the prediction model. All the daily data for the 10 years was accounted for, summarised, and used to determine the average monthly brokerage fee paid for comparative purposes. The author then compared this average historical monthly brokerage data against the predicted fixed future monthly brokerage. The author assumed that the client would choose a lower monthly brokerage fee based on the same service as currently being received.

This addressed the **second null hypothesis**: There is no difference in South African stockbroking clients when choosing a payment option.

H2a: Stockbroking clients will prefer to pay a fixed monthly subscription.

H2b: Stockbroking clients prefer to pay a transaction-based variable fee per transaction.

The author used prospect theory (PT) to predict client behaviour, as discussed in the literature review and Chapter Three. Clients will opt for the highest value (V), which refers to the most favourable brokerage payment option. Each decision involves a probability (p) and a weighted decision factor π(p), under the condition that if $p + q$ equals 1, then either $x > y > 0$ or $x < y < 0$, as detailed in Equation 1.

The author presented a scenario where a stockbroking client had two options when comparing their historical monthly brokerage charges to the proposed fixed fee. If the client's current fee exceeds the new monthly subscription, they will choose the fixed monthly fees. On the other hand, if the historical brokerage fees are lower than the new monthly subscription, they will not opt for the new subscription model.

Table 6.1: Historic brokerage fees on the same sample client set

acc_cde	Total Months	Total value	Av Monthly fee	Monthly Rand spend
A	17	4429259	260544,65	R2 605,45
B	7	245720	35102,86	R351,03
C	38	2621887	68997,03	R689,97
D	69	8133000	117869,57	R1 178,70
E	17	483682	28451,88	R284,52
F	111	25589966	230540,23	R2 305,40
G	81	39655558	489574,79	R4 895,75
H	53	3686942	69564,94	R695,65

Table 6.1 shows a summarised version of the actual historical brokerage paid over the 10 years. Total months gives the number of months where the client made transactions. Total value is the summation of all data, then divided by the number of months to determine the monthly average brokerage fee paid. This was then divided by 100 to convert to a monthly Rand amount.

Table 6.2: Monthly fixed predicted brokerage vs historic monthly variable fees

acc_cde	Monthly Rand Prediction	Historic Monthly fee	Client Value	Hypothesis choice
A	R8 108,82	R2 605,45	Lower	H2b
B	R11 223,15	R351,03	Lower	H2b
C	R1 063,40	R689,97	Lower	H2b
D	R1 374,71	R1 178,70	Lower	H2b
E	R2 627,58	R284,52	Lower	H2b
F	R2 607,26	R2 305,40	Lower	H2b
G	R3 244,28	R4 895,75	Higher	H2a
H	R2 457,70	R695,65	Lower	H2b

Table 6.2 compares the fixed monthly subscription price unique to each client provided by the model and the historic monthly variable fees. Client value is considered lower if the new predicted fixed monthly fee is higher than the historical monthly average brokerage fees paid. The hypothesis choice column relates to whether there is a higher value to clients. Clients select the new fixed monthly fee if there is a higher value; therefore, hypothesis H2a applies to them. Should the client experience a lower value, they will remain on the historic variable rate fee, with Hypothesis H2b applicable to them. The results showed that only client G would select the new fixed subscription brokerage model, as the predicted monthly fixed fee of R3 244.28 is lower than the historic monthly fees of R4 895.75. The model had a 12.5% success rate in predicting a fixed fee that would be chosen over the historic variable fees on this specific random sample.

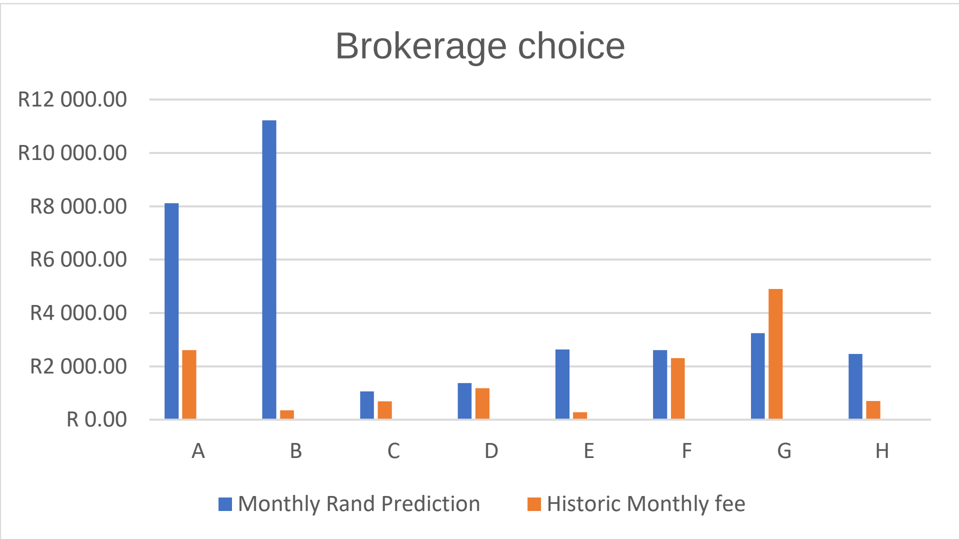


Figure 6.1: Monthly prediction vs historic fees

During the period, clients A, B and E had the fewest number of trades. It was observed that there were significant differences between the predicted amounts and the historical fees for these clients. On the other hand, clients who traded more frequently had more accurate predictions. A decision was thus reached, leading to the rejection of the null hypothesis. Consequently, it was determined that H2b, which posits that stockbroking clients favour a transaction-based variable fee per transaction, applied to seven clients. Client G applied to the alternative hypothesis H2a: Stockbroking clients prefer fixed monthly subscriptions.

Chang and Nichols (1987) use PT in their tax audit risk paper, demonstrating the applicability to payments and not just income, where a tax payment can be perceived as a gain or a loss depending on the individual. The author agrees with this statement and applies it to stockbroking brokerage fees. The lower the fees, the more the perceived gain to the client. The author believes that a fixed monthly fee could better align with client preferences than the current variable fee model, even though the results showed that clients would choose the historic transaction-based variable rate model. Vaska and colleagues (2020) final finding on value capture is that transaction-based revenue models are not viable for long-term application.

Here is a summary of some apparent beneficial differences that have been touched on for the fixed subscription price versus the old transactional-based brokerage from a client perspective:

I. Cost predictability – while the services remain the same for the online stockbroking client.
II. More cost efficiency for active traders – a fixed monthly fee for active traders can provide cost savings, as seen for Client G.
III. Simplicity and transparency – it is easy for clients to understand the cost of their trading activities and also easier for authorities to monitor compliance.
IV. Trading preferences – can vary depending on trading strategies, with the larger trade values the client holds influencing their choice. Clients A, B and E will prefer a variable rate, as observed in Table 6.1, due to their low trading volumes. At the same time, active traders might choose a fixed monthly fee depending on their frequency and transaction size.

Ultimately, suitability depends on the individual client's trading preference and frequency while balancing cost and convenience to their specific trading strategies.

4.6.1 Summary of Customer Decision-Making

Having analysed the same set of eight random clients, the author will now take all transactions into account over the entire 10-year period, grouping them into monthly amounts and finding a monthly average of actual historic brokerage paid. These historic brokerage amounts are compared to the predicted fixed monthly fees. The author noticed that clients who traded more frequently had a model that predicted a fixed monthly value closer to their historical fees.

The null hypothesis was **rejected**, and seven clients chose **H2b:** Stockbroking clients prefer to pay a transaction-based variable fee per transaction. At the same time, there was one client, G, where the alternative hypothesis **H2a** applied: Stockbroking clients will prefer to pay a fixed monthly subscription.

The author believes a fixed monthly subscription amount will better suit clients trading online more frequently, looking for cost efficiencies and predictability. In the next chapter the author summarises the case study's findings, answers all the research questions, states the final hypotheses and concludes the study. Additionally, suggestions will be made regarding areas that can be improved and further research that can be carried out to enhance the body of knowledge in this field of study.

CHAPTER 5. CONCLUSIONS AND RECOMMENDATION

5.1 Introduction

In this final chapter, the author relates the study's findings to each of the two research questions and elaborates on how they have been addressed. Recommendations are made to stakeholders based on what was discovered. Furthermore, the author suggests further research that can be carried out in the future to add to this body of knowledge and address some limitations of this work.

Problems addressed by the study:

This study sought to address two practical problems faced by South African online stockbrokers. Problem 1: Currently, online stockbrokers primarily compete against each other by lowering their transaction-based brokerage rates. How do online stockbroking platforms replace this loss in fees? Problem 2: Traditional transaction-based brokerage models were designed before implementing digital trading through online platforms. The author has answered the following two research questions to address the practical problems being experienced:

1. What are the effects of time periods, trading frequency and transaction values on brokerage rates?

2. What are the differences between a subscription-based payment model and the existing transaction-based model on brokerage rates?

Hypotheses tested:

This study aimed to test the following hypotheses:

I. **Null Hypothesis 1**: There is no relationship between time periods, trading frequency, transaction value, and their effect on brokerage rates.

II. **Null Hypothesis 2**: There is no difference to South African stockbroking clients when choosing a payment option.

H2a: Stockbroking clients will prefer to pay a fixed monthly subscription.

H2b: Stockbroking clients prefer to pay a transaction-based fee per transaction.

5.2 Conclusion

5.2.1 Time periods, trading frequency and transaction values on brokerage rates

The author addressed the first research question concerning the impact of time periods, trading frequency, and transaction values on brokerage rates. The conclusion drawn was that both frequency and transaction values exert an influence on brokerage rates.

The descriptive statistics results yielded valuable insights into the predominant concentration of brokerage values at R70.00 and below. Yearly distributions indicated that between 40% and 51% of trade executions would incur a brokerage charge lower than R70.00 over the 10-year period. The brokerage intervals were skewed to the lower end, with R70.00 and below accounting for most executions. Transaction value had a smooth distribution of intervals, with no interval accounting for more than 20% of the executions in a year.

Through inferential analysis, the author tested independent and dependent variable relationships using a Chi-square test for association. The results showed no relationships with time periods; however, there were significant relationships between transaction values and frequency. It was therefore observed that those trades attracting R70.00 or lower brokerage only needed one trade (frequency) to complete the deal, while trades in the highest brokerage interval of R336.01 or more required three or more trades to complete the deal on average.

The results related to the initial research question indicate that there is no significant association between time periods and brokerage rates. Secondly, there are significant relationships established and tested between frequency, transaction values and the dependent variable brokerage. The alternative hypothesis is true for frequency and transaction values. Subsequently, these two important relationships were employed in the subsequent analysis to establish the foundation for a fixed subscription price and an empirical specification. Yearly impacts stemming from local and global economies, the COVID-19 pandemic, international investment flow, and the scale of online stockbrokers were observed.

5.2.2 Differences between a subscription-based payment model and the existing transaction-based model on brokerage rates

The second research question deals with the distinctions between the subscription-based payment model and the prevailing transaction-based model concerning brokerage rates. Considering the aforementioned, the author emphasises the preference for lower fees within a monthly timeframe as a greater value proposition for the client. Using time series analysis to address the second research question, it was noted that clients opted for the existing variable fee in seven out of eight instances.

In line with existing literature, this research recommends a fixed monthly subscription fee along with numerous others (Clauss, 2017; Croxson et al., 2021; Petri, 2014; Ramdani et al., 2020). The author also agreed with the various advantages of a platform model, as evidenced by others (Rohn et al., 2021; Croxson et al., 2021). In the future, the focus will be on promoting or capturing specific network effects seen in superior platform models, leading to exponential growth.

To address the second research question, the findings of this research determined that a daily model provided a better fit when compared to modelling a monthly prediction. However, the accuracy was closer to the actual amounts by making a monthly adjustment based on the daily model prediction. Similar findings were made by Pagano et al. (2021), where higher participation affected trading quality, especially in volatile times.

Secondly, it was found that an online stockbroking client chooses a monthly brokerage rate, whether fixed or variable, based on the best value for the client's needs. In this case, the lowest price would provide the highest value. This assisted in determining that there was a 12.5% probability a client would choose the model's fixed rate on that specific random sample. The author observed that the greater the prediction accuracy from the model, the higher the number of transactions also observed (Ingrassia, 2021). A fixed monthly subscription can offer cost efficiencies and transparency to the online stockbroking platform and the trading client, which was also observed by Ramdani et al. (2020) and Rochet and Tirole (2006). However, clients tend to choose the cheapest brokerage that offers the same level of service, as it provides the most value, as Ingrassia (2021) observed. Although fixed monthly subscriptions offer numerous benefits, seven out of eight random clients sampled preferred the old variable rate model due to its better value.

5.3 Recommendations

Form the findings of the study, it is recommended that adopting fixed monthly fees over variable fees charged by online stockbrokers in South Africa will be feasible. The results, however, did not indicate that this approach would be more widely accepted. An online bank offering stockbroking services may consider introducing a fixed monthly fee for an all-inclusive banking and stockbroking package, which would be a first in South Africa. For new providers of online stockbroking platforms, considering this fixed monthly fee could assist to distinguish their platforms from the competition.

The findings of this research provide a better understanding of the South African online stockbroking industry, particularly its revenue model. It suggests that platform models can be successful in this market and proposes that a flat monthly subscription fee would make it easier for authorities to monitor costs and profits as per the Financial Markets Act. This would also ensure more accurate disclosure of information related to specific financial terms.

When implementing revenue model changes, the author recommends a phased approach that considers the willingness of staff, clients and the market to accept the change. It is crucial to undertake a change management process before implementation to ensure a smooth transition. To conclude, the author suggests adding further parameters to the fixed-term monthly fee the model predicts. This should not be open-ended and include a limit on the number of trades and transaction value per trade. Using the averages determined in this dataset, one could suggest two trades per month with a transaction value of R55 000 per trade, leaving clients with a R110 000-per-month transaction limit.

5.4 Suggestions for Further Research

From the findings of this study, it is suggested that further research be conducted on the following points, which will assist in expanding existing literature.

I. Online platforms can utilise their customers' data and advanced algorithms to determine everyone’s reservation price and offer personalised pricing slightly below each client’s threshold brokerage rate. This practice, known as ‘value-extracting innovation’, may be considered monopolistic conduct, according to Croxson et al. (2021). However, this may provide greater efficiency and closer matching of brokerage fees clients are willing to pay.

II. There is a need to more comprehensively account for all stockbroking costs, both fixed and variable, to run the entire platform to provide a more accurate idea of what fixed monthly fee is required to run profitably and sustainably.

III. The author’s final empirical model only contained two independent variables; additional variables can be added to improve the accuracy of this model.

IV. The potential for South Africa to adopt alternative off-exchange trading practices, akin to payment for order flow methods utilised by platforms such as Robinhood, serving as their primary source of revenue.

V. The extent to which online stockbrokers can rely on platform models and the likelihood of their success based on the recent adoption of such models in the financial and banking industries.

VI. The extent to which network effects can assist growth should online stockbrokers successfully implement a platform model and community.

VII. What the tax implications would be, considering that online stockbroking clients would now be paying a platform fee and not a variable brokerage fee based on trading.

Further research can provide comprehensive value to the entire stockbroking value chain in South Africa. This will contribute to the limited number of peer-reviewed publications on stockbroking and revenue models used in South Africa.

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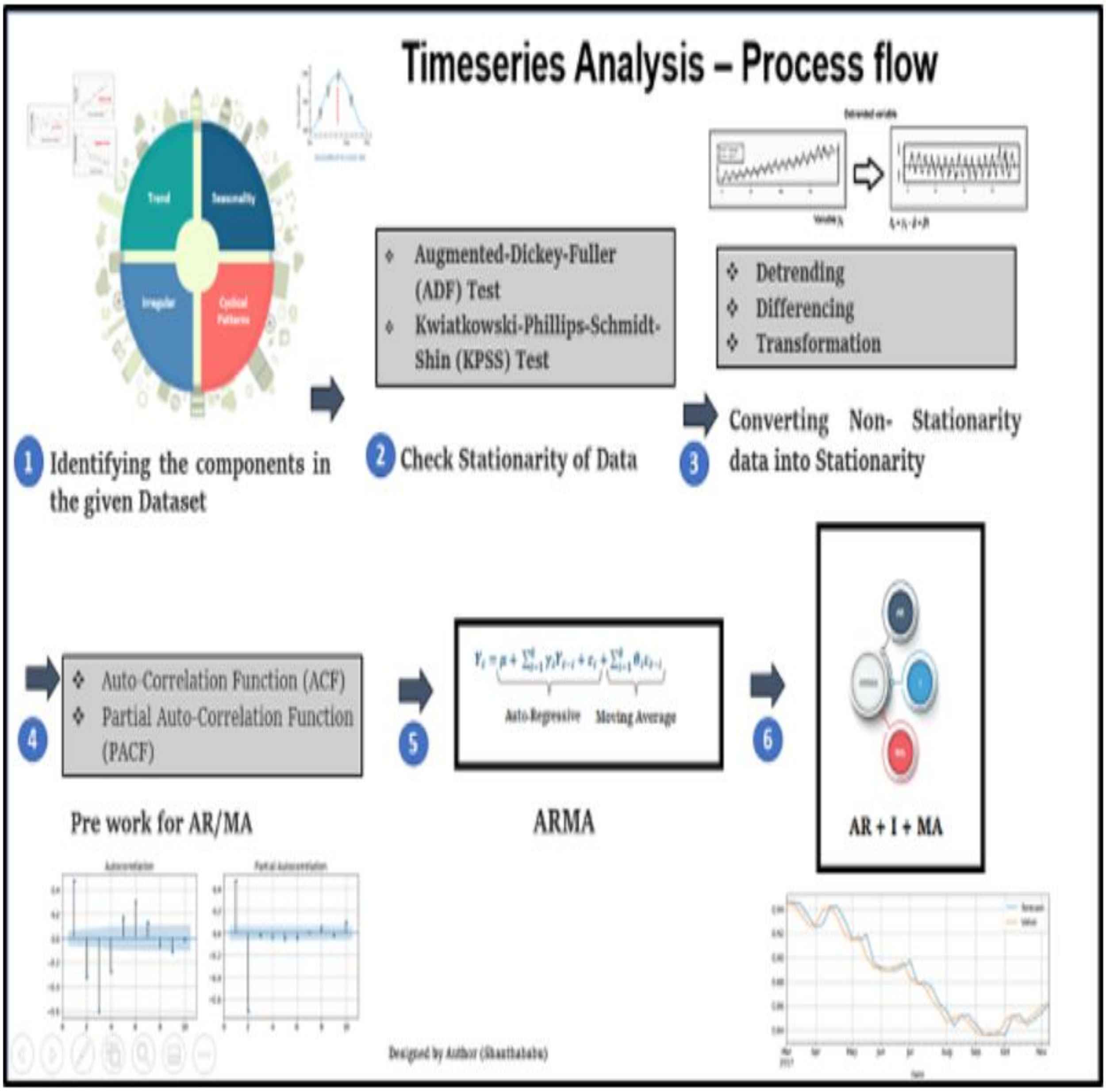
Appendices

Appendix A: Time-series analysis process flow



Appendix B: R-code for time-series testing

Steps	Code

Step 1: Install libraries	requiredPackages = c('dplyr',"purrr",'ggplot2','readxl','tidyverse', 'latexpdf' ,'lubridate',
	'readr','reshape2','data.table','broom','anytime','DT',
	'knitr','ggfortify','Metrics','fitdistrplus','Hmisc',
	'formattable','haven','pillar','systemfit','plm','pder',
	'pcse', 'vars','tsbox', 'svars','ggfortify',
	'lpirfs',"gridExtra",'readxl','ggplot2', 'zoo')
	for(p in requiredPackages){
	if(!require(p,character.only = TRUE)) install.packages(p)
	library(p,character.only = TRUE)
	}

Step 2: Import libraries	library(tseries) library(dplyr) library(gridExtra) library(ggpubr) library(readxl) library(vars) library(mice) library(ggplot2) library(zoo) library(vars) library(cowplot) library(gridExtra) library(gridGraphics) library(readxl) library(dynlm) library(forecast) library(BVAR) library(ggplot2) set.seed(42)

Importing data	`bdata <- read_excel("C:/Users/abjn721/Downloads/BESTER'S RESEARCH DATA.xlsx")` `bdata.`

Data preparation I	`bdata1<-unique(bdata[,c("order_date_2","day","YearMonth","order_date","chg_bro","del_seq","Absolute_Tx_amount","weekday","mnth","yr")])`
	
	`bdata2<-unique(bdata1%>%group_by(order_date)%>%summarise_all("mean"))`
	`bdata7<-unique(bdata1%>%group_by(weekday)%>%summarise_all("mean"))`
	`bdata3<-unique(bdata2[,c("order_date","chg_bro","del_seq","Absolute_Tx_amount")])`
	`bdata3`

Plotting original and differenced time series	`ggplot(bdata2, aes(order_date_2,chg_bro)) + geom_line() + ylab("Brokarage") +`
	`  xlab("date")+`
	`  ggtitle("Original Brokarager Trend")`
	
	`ggplot(bdata6, aes(order_date_2,dl_chg_bro)) + geom_line() + ylab("Brokarage") +`
	`  xlab("date") +`
	`  ggtitle("differenced Brokarager")`
	
	`ggplot(bdata2, aes(order_date_2, del_seq)) + geom_line() + ylab("del_seq") +`
	`  xlab("date")+`
	`  ggtitle("original del_seq trend")`
	
	`ggplot(bdata6, aes(order_date_2, d_del_seq)) + geom_line() + ylab("del_seq") +`
	`  xlab("date")+`
	`  ggtitle("differenced del_seq")`
	
	`ggplot(bdata2, aes(order_date_2, Absolute_Tx_amount)) + geom_line() + ylab("absolaute transaction amount") +`
	`  xlab("date")+`
	`  ggtitle("original absolute transaction amount trend")`
	
	`ggplot(bdata6, aes(order_date_2, dl_Absolute_Tx_amount)) + geom_line() + ylab("absolaute transaction amount") +`
	`  xlab("date")+`
	`  ggtitle("differenced absolute transaction amount")`

Box and Whisker plots for outliers	`# Brokarage`
	`ggplot(bdata6, aes(y=dl_chg_bro, x = yr)) +`
	`  geom_boxplot(aes(group=yr)) +`
	`  scale_x_continuous(breaks=seq(0,12,1)) +`
	`  ggtitle("Brokarage by Year")`
	
	`ggplot(bdata6, aes(y=dl_chg_bro, x = mnth)) +`
	`  geom_boxplot(aes(group=mnth)) +`
	`  scale_x_continuous(breaks=seq(0,12,1), labels=c("","Jan","Feb","Mar",`

	"Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec")) +
	  ggtitle("Brokarage by Month")
	
	# trans
	ggplot(bdata6, aes(y=dl_Absolute_Tx_amount, x = yr)) +
	  geom_boxplot(aes(group=yr)) +
	  scale_x_continuous(breaks=seq(0,12,1)) +
	  ggtitle("absolute transaction amount by Year")
	
	ggplot(bdata6, aes(y=dl_Absolute_Tx_amount, x = mnth)) +
	  geom_boxplot(aes(group=mnth)) +
	  scale_x_continuous(breaks=seq(0,12,1), labels=c("","Jan","Feb","Mar",
	"Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec")) +
	  ggtitle("absolute transaction amount by Month")
	
	# del_seq
	ggplot(bdata6, aes(y=del_seq, x = yr)) +
	  geom_boxplot(aes(group=yr)) +
	  scale_x_continuous(breaks=seq(0,12,1)) +
	  ggtitle("del_seq by Year")
	
	ggplot(bdata6, aes(y=del_seq, x = mnth)) +
	  geom_boxplot(aes(group=mnth)) +
	  scale_x_continuous(breaks=seq(0,12,1), labels=c("","Jan","Feb","Mar",
	"Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec")) +
	  ggtitle("del_seq by Month")
	
	# interaction between transaction amount & Frequency
	ggplot(bdata6, aes(y=dl_abs_amt_x_d_del_seq, x = yr)) +
	  geom_boxplot(aes(group=yr)) +
	  scale_x_continuous(breaks=seq(0,12,1)) +
	  ggtitle("Frequency & transaction interaction by Year")
	
	ggplot(bdata6, aes(y=dl_abs_amt_x_d_del_seq, x = mnth)) +
	  geom_boxplot(aes(group=mnth)) +
	  scale_x_continuous(breaks=seq(0,12,1), labels=c("","Jan","Feb","Mar",
	"Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec")) +
	  ggtitle("Frequency & transaction interaction by Month")

Augmented Dickey-Fuller Test	adf_chg<-adf.test(bdata6$dl_chg_bro) adf_absT<-adf.test(bdata6$dl_Absolute_Tx_amount) adf_del<-adf.test(bdata6$d_del_seq)
KPSS test	kpss_chg<-kpss.test(bdata6$dl_chg_bro, null="Trend") kpss_abs<-kpss.test(bdata6$dl_Absolute_Tx_amount, null="Trend") kpss_del<-kpss.test(bdata6$d_del_seq, null="Trend")
Autocorelation & partial autocorrelation	plot(acf(bdata6$chg_bro,pl=FALSE), main = "Original chg_bro") plot(acf(bdata6$dl_chg_bro,pl=FALSE), main = "Differenced chg_bro")

	`plot(acf(bdata6$Absolute_Tx_amount,pl=FALSE), main = "Original absolute transaction amount")`
	
	`plot(acf(bdata6$dl_Absolute_Tx_amount,pl=FALSE), main = "Differenced absolute transaction amount")`
	
	`plot(acf(bdata6$del_seq,pl=FALSE), main = "Original frequency")`
	
	`plot(acf(bdata6$d_del_seq,pl=FALSE), main = "Differenced frequency")`
	
	`plot(pacf(bdata6$chg_bro,pl=FALSE), main = "Original brokerage")`
	
	`plot(pacf(bdata6$dl_chg_bro,pl=FALSE), main = "Differenced brokerage")`
	
	`plot(pacf(bdata6$Absolute_Tx_amount,pl=FALSE), main = "Original absolute transaction amount")`
	
	`plot(pacf(bdata6$dl_Absolute_Tx_amount,pl=FALSE), main = "Differenced absolute transaction amount")`
	
	`plot(pacf(bdata6$del_seq,pl=FALSE), main = "Original frequency")`
	
	`plot(pacf(bdata6$d_del_seq,pl=FALSE), main = "Differenced frequency")`

Fitting model	`bdata8 <- as.ts(bdata6)`
	`bdata6$dl_chg_bro<- as.ts(bdata6$dl_chg_bro)`
	`mod1_lm<-lm(dl_chg_bro ~ dl_Absolute_Tx_amount + d_del_seq +dl_abs_amt_x_d_del_seq+weekday+mnth+yr+day, data=bdata6)`
	`summary(mod1_lm)`
	
	`#R squared adjusted 0.441`
	`mod2_tslm <- tslm( dl_chg_bro~ dl_Absolute_Tx_amount + d_del_seq+ dl_abs_amt_x_d_del_seq+weekday+mnth+yr+day, data=bdata8)`
	`summary(mod2_tslm)`
	
	`#perfect fit, R squared equals 1, may be unreliable`
	`mod3_dynlm <- dynlm(dl_chg_bro ~ dl_Absolute_Tx_amount + d_del_seq+dl_abs_amt_x_d_del_seq+weekday+mnth+yr+day, data = bdata6)`
	`summary(mod3_dynlm)`
	
	`# Arima`
	
	`dl_chg_bro <- as.ts(bdata6$dl_chg_bro)`
	`mod4_arima<-auto.arima(dl_chg_bro, seasonal=FALSE)`
	`summary(mod4_arima)`

Comparing linear prediction to actual	`fit1 <- predict(mod1_lm)`
	
	`plot(bdata6$dl_chg_bro,type="l",col="black",panel.first=grid(), xaxt="n", main="Actual vs Predicted, by day")`
	`axis(1, at = seq(0, 2686, by = 1), las=3)`
	`lines(fit3,col="red")`
	`lines(fit4,col="green")`

	legend("topright",legend=c("black - Actual","red - Linear regression, R.sq 0.85", "green - ARIMA model (default), R.sq 0.40"))
Residual sum of squares:	RES<-data.frame(Res_lm=numeric(2687), Res_dynlm = numeric(2687), Res_arima = numeric(2687)) #tslm excluded here, due to unreliable model output (R squared equalled 1, no errors) RES$Res_lm<-mod1_lm$residual RES$Res_lm <- RES$Res_lm*RES$Res_lm #RES$Res_dynlm <- c(0,0,mod3_dynlm$residuals) RES$Res_dynlm <- RES$Res_dynlm * RES$Res_dynlm RES$Res_arima <- mod4_arima$residuals RES$Res_arima <- as.numeric(RES$Res_arima) RES$Res_arima <- RES$Res_arima * RES$Res_arima RES_comp <- as.list(c(sum(RES$Res_lm), sum(RES$Res_arima))) RES_comp <- as.data.frame(RES_comp) colnames(RES_comp) <- c("lm","arima") RES_comp

Appendix C: Augmented Dickey-Fuller Test

Variable	Dickey-Fuller	Lag order	p_{value}
Original (chg_bro)	-3.0777	5	More than 0.05
Differenced (chg_bro)	-8.2314	5	Less than 0.05
Original (abs trans amount)	-3.6561	5	More than 0.05
Differenced (abs trans amount)	-8.1847	5	Less than 0.05
Original (del_seq)	-2.7638	5	More than 0.05
Differenced (del_seq)	-8.7629	5	Less than 0.05

Appendix D: Random sample of client to predict fixed fees

acc_cde	del_seq	chg_bro	Absolute T	Order date	interaction	YEAR	Month	Weekday	day	Predictior	Differenc	VaR adjus	Daily Ranc	Monthly Predi	Monthly Rand R
A	1	43064	61016,47	2013/01/02	61016,47	1	1	4	2	40544,12	-2519,879	decrease	R405,44	810882,42	R8 108,82
B	1	59612	84466,92	2015/02/27	84466,92	3	2	6	27	56115,73	-3496,265	decrease	R561,16	1122314,69	R11 223,15
C	1	7000	7961,66	2017/10/10	7961,66	5	10	3	10	5317,01	-1682,986	decrease	R53,17	106340,29	R1 063,40
D	1	7131	10306,13	2017/10/11	10306,13	5	10	4	11	6873,55	-257,455	decrease	R68,74	137470,90	R1 374,71
E	1	13666	19739,73	2019/01/28	19739,73	7	1	2	28	13137,89	-528,112	decrease	R131,38	262757,76	R2 627,58
F	3	14040	20257,79	2019/01/28	60773,37	7	1	2	28	13036,30	-1003,697	decrease	R130,36	260726,06	R2 607,26
G	3	12503	25221,24	2020/06/23	75663,72	8	6	3	23	16221,42	3718,422	Increase	R162,21	324428,45	R3 244,28
H	1	13034	18460,58	2020/06/23	18460,58	8	6	3	23	12288,48	-745,520	decrease	R122,88	245769,60	R2 457,70