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Abstract

Load shedding was first introduced in South Africa in October 2007 as a strategy to manage grid overload caused by increasing electricity demand that is surpassing supply, exacerbated by inadequate infrastructure maintenance. The economic repercussions of load shedding have been significant, particularly for various sectors of South Africa's economy. In 2023, the South African Property Owners Association conducted a survey on the impact of load shedding on the commercial real estate industry and its cost implications. This study aims to investigate the impact of load shedding on South Africa's Real Estate Investment Trusts (SA REITs) during the period from 2019 to 2023. Using the Autoregressive Distributed Lag (ARDL) model as the primary analytical tool, the study seeks to assess both the short- and long-term relationships between load shedding and South African REIT performance. Additionally, the Arbitrage Pricing Theory (APT) model is employed to examine the influence of macroeconomic factors on the returns of two REIT portfolios, with a specific focus on the effect of load shedding as a risk factor. The analysis evaluates the factor sensitivities and risk premiums associated with each macroeconomic factor. The results from the ARDL model indicate no significant long-term relationship between load shedding and REIT returns; however, the short-term analysis shows a positive, though statistically insignificant, relationship. Similarly, the APT model reveals that the load shedding factor is insignificant for both REIT portfolios, suggesting that the overall effect of load shedding on REIT returns remains inconclusive.

Keywords: Load Shedding, South Africa’s Real Estate Investment Trusts, Autoregressive Distributed Lag Model, Arbitrage Pricing Theory, Macroeconomic Factors.

Declaration

I, Thandeka Thembelihle Mdakane, student number 812720, declare that this Thesis Report is my own work and that it has not been submitted to any other college or university for the award of academic credit.

Signature of Student

Mdakane

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Date

21 August 2024

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Above all, and most importantly, I thank Jehovah Almighty for helping me get through this research.

Dedication

Dedicated to me.

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List of symbols and Abbreviations

$	United States Dollar
APT	Arbitrage Pricing Theory
ARDL	AutoRegressive Distributed Lag
ARIMA	Lag Regression Autoregressive Integrated Moving Average
ADF	Augmented Dickey Fuller
AIC	Akaike information criterion
BCO	Brent Crude Oil Prices
CAPM	Capital Asset Pricing Model
CPI	Consumer Price Index
EPRA	European Real Estate Association
EEDC	Enugu Electricity Distribution Company
EXP	Export
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GMM	Generalised Method of Moments
GP	Gold Prices
IMP	Imports
JSE	Johannesburg Stock Exchange
MS	Money Supply
MWs	Megawatts
NAREIT	National Association of Real Estate Investment Trusts
NAV	Net Asset Value
OCLF	Operational Capability Loss Factor
OLS	Ordinary Least Squares
PCLF	Planned Capability Loss Factor
PLS	Property Loan Stock
PP	Phillips-Perron

PUT	Property Unit Trusts
R	South African Rand
REITs	Real Estate Investment Trust
RRt	REIT’s monthly stock price movement
SA REIT	South African REIT
SADC	Southern African Development Community
SAPOA	South African Property Owners Association
SAPP	Southern African Power Pool
SARB	South Africa Reserve Bank
SONA	State of the Nation Address
UCLF	Unplanned Capability Loss Factor
USA	United States of America
VIF	Variance Inflation Rate Factor
ZAR_USD	Dollar to Rand

1. Introduction

The Real Estate Investment Trust (REIT) structure was first established in the United States of America (USA) in 1960, when Congress passed the REIT Act. This act allowed for the creation of a new type of investment vehicle that enabled investors to pool their capital for investment in a diversified portfolio of real estate assets (Securities and Exchange Commission, 2019). A REIT company owns a portfolio of income-generating real estate properties, enabling individual investors to own shares in the portfolio without directly owning any real estate assets (Naidoo, 2014). The purpose of the REIT Act was to provide investors with the opportunity to invest in large-scale and income-producing real estate without the need to directly purchase or manage properties (South Africa National Treasury, 2007). Before the introduction of REITs, commercial real estate investment opportunities were mainly available to financial intermediaries and affluent individuals. However, REITs have democratized access, enabling ordinary individuals to participate in these investment opportunities. REIT assets encompass a variety of types, including offices, residential properties, healthcare facilities, retail spaces, hotels, and property infrastructure such as fiber cables, cell phone towers, and storage facilities (NAREIT, 2022).

According to statistics released by the National Association of Real Estate Investment Trusts (NAREIT) in December 2021, the USA had the world's largest REIT market, hosting 10 of the largest REITs globally. In the same year, 41 countries adopted the USA-based REIT market model and listed REITs on their respective stock exchanges. The combined market capitalization of these REITs exceeded $500 billion (NAREIT, 2021). Globally, there are 893 listed REITs contributing to a significant global REIT GDP of $98 trillion. One of the appealing features of REITs is their obligation to distribute a substantial portion of taxable income to shareholders as dividends, making them an attractive investment option for individuals seeking steady income streams (NAREIT, 2021).

The South African REIT (SA REIT) is a listing instrument established in 2013 on the Johannesburg Stock Exchange (JSE), following the enactment of REITs legislation. This legislative development marked a significant milestone for the South African property market, providing a regulatory framework for the establishment and operation of REITs. Prior to the introduction of SA REITs, South Africa had two primary forms of property investments: property loan stock (PLS) companies and property unit trusts (PUT) (Ntuli & Omokolade, 2017), both governed under the oversight of the Financial Services Board. PUTs were governed by the Collective Investment Schemes Control Act (National Treasury, 2012), whilst PLS companies adhered to the Companies Act and JSE regulations. As a result, the regulation of the listed property sector was fragmented and tax treatment between the two structures differed (Kantilal, 2016), adversely affecting investment confidence. The PUT and PLS structures have since been transformed to SA REITs. According to a recent report by JLL (2021), the total market capitalization of South African REITs in 2021 was over ZAR 500 billion. This represents a significant increase from the market capitalization of ZAR 8 billion in 2001, when the first listed PUTs were established in the country. South Africa has 33 listed REITs and 3 non-SA REITs listed on the JSE. The European Public Real Estate Association reported that SA REITs' total market capital is US$14.37 billion as of December 2022.

South Africa reported a nominal gross domestic product (GDP) of R6.64 trillion at the end of 2022, marking a R446 billion increase from 2021. The finance, real estate, and business services sector contributed R1.1 trillion, reflecting a 3.9% rise compared to 2021 (Stats SA, 2022). The market capitalization of SA REITs reached R241.1 billion by the end of 2022. According to Ntuli and Omokolade (2017), in 2014, SA REITs outperformed all asset classes, including South African equities and bonds, as well as UK, European, and Asian REITs.

One of the factors that make REITs a preferred investment is their dividend distribution policy. The primary sources of returns from REITs are dividend yield and share price appreciation. The dividend yield serves as a metric for evaluating the performance of investments, including those in REITs, within the stock or capital market. This metric can be expressed as a percentage or in monetary units (Olanrele, 2014) According to the JSE policy, REITs must distribute at least 75% of their net taxable earnings available as dividends to investors. REITs are subject to special tax treatment as they are shielded against corporate income tax (Gyourko and Sinai, 2003) due to their high dividend payout. SA REITs are subject to section 25BB of the Income Tax Act (SARS Interpretation Note 97, 2022) which includes tax benefits and exemptions for qualifying distributions made by REITs to their shareholders. Dividends received from REITs may also be subject to dividend withholding tax at a rate that may differ from other types of dividends.

South African REITs have contended with persistent challenges posed by load shedding. Load shedding involves the deliberate shutdown of power supply to specific areas of the country, aimed at alleviating strain on the electricity grid and preventing a collapse (Lawson, 2020). In South Africa, Eskom serves as the primary national state-owned electricity supplier, providing approximately 91% of the country's total electricity, with around 5% exported through the Southern African Power Pool (SAPP). According to a 2022 report by Eskom, the state-owned utility operates as a vertically integrated entity across a value chain that supplies electricity not only to South Africa but also to the Southern African Development Community (SADC) region. The integrated grid connects the SAPP, which encompasses South Africa, Botswana, eSwatini, Lesotho, Mozambique, Namibia, Zambia, and Zimbabwe (Eskom, 2022).

Load shedding was first implemented in October 2007. Mbomvu, et al (2020) explain that load shedding is caused by the neglect of infrastructure maintenance and the rising demand that the supply cannot meet. Some outages are scheduled in advance and communities are notified prior to outages occurring while, in other cases, load shedding happens without warning. In December 2019 and in May 2023, Eskom implemented “Stage 6” electricity cuts which meant a reduction of approximately 6,000 megawatts (MW) of production, the biggest reduction in Eskom’s history. Energy cuts had previously only gone to Stage 4 at maximum roughly 4,000 MW production drop. The National Energy Regulator of South Africa was presented with the draft NRS048-9 Edition 3 document for approval. The document proposes updated load shedding codes with up to 16 stages, with the highest stage involving 24 hours of power outages in a 32-hour cycle. This represents a significant increase from the Edition 2 document, which includes load shedding codes with up to 8 stages, involving a maximum of 16 hours of power cuts in a 32-hour cycle. Thus, the implementation of the NRS048-9 Edition 3 document could see South Africa face power outages lasting anywhere from one hour to 24 hours over a 32-hour period. In the 2023 State of the Nation Address (SONA), President Cyril Ramaphosa announced the appointment of Dr. Kgosientso Ramokgopa as the Minister of Electricity, tasked to specifically address South Africa’s ongoing energy crisis.

Load shedding data consists of the Unplanned Capability Loss Factor (UCLF), also known as outages, which represent instances when a unit was out of service and are measured in megawatts. The megawatt value determines the extent of load shedding. Eskom’s website explains the 8 load shedding schedules that have been developed based and how they are implemented:

1. “Stage 1 load shedding means that up to 1000MW of capacity needs to be shed. Consumers can expect to be shed up to 3 times over a four-day period for two hours at a time, or 3 times over an eight-day period for four hours at a time.

2. Stage 2 load shedding means that up to 2000MW of capacity needs to be shed. Consumers can expect to be shed up to 6 times over a four-day period for two hours at a time, or 6 times over an eight-day period for four hours at a time.

3. Stage 3 load shedding means that up to 3000MW of capacity needs to be shed. Consumers can expect to be shed up to 9 times over a four-day period for two hours at a time, or 9 times over an eight-day period for four hours at a time.

4. Stage 4 load shedding means that up to 4000MW of capacity needs to be shed. Consumers can expect to be shed up to 12 times over a four-day period for two hours at a time, or 12 times over an eight-day period for four hours at a time.

5. Stage 5 load shedding means that up to 5000MW of capacity needs to be shed. Consumers can expect to be shed up to 12 times over a four-day period - 9 times for 2 hours and 3 times for 4 hours.

6. Stage 6 load shedding means that up to 6000MW of capacity needs to be shed. Consumers can expect to be shed up to 12 times over a four-day period - 6 times for 2 hours and 6 times for 4 hours.

7. Stage 7 load shedding means that up to 7000MW of capacity needs to be shed. Consumers can expect to be shed up to 12 times over a four-day period - 3 times for 2 hours and 9 times for 4 hours.

8. Stage 8 load shedding means that up to 8000MW of capacity needs to be shed. Consumers can expect to be shed up to 12 times over a four-day period for four hours at a time.”

According to Walsh et al. (2021), load shedding has cost the South African economy nearly R35 billion between 2007 and 2019. Moreover, their estimates suggest that if all the load shedding experienced in the first quarter of 2019 had occurred between 2007 and 2019, the country's economy would have contracted by 5% in real GDP. The implementation of load shedding has led to an increase in business operational costs, as either the tenant or the property owner needs to invest in alternative power sources to ensure the continuity of production during power outages (Cokayne, 2023). The South African Property Owners Association (SAPOA) conducted a survey on the impact of load shedding on the commercial real estate industry. Some of the results from the survey were as follows:

83.05% of property companies registered with SAPOA indicated they had diesel generators, and 49.15% had solar energy installations as their preventative measures to combat load shedding. This indicates that businesses have implemented both diesel generators and solar solutions. Additionally, some companies have invested heavily in inverters. The consequences of load shedding are not limited to direct costs; they also include indirect expenses such as reduced labour productivity and damage to machinery.

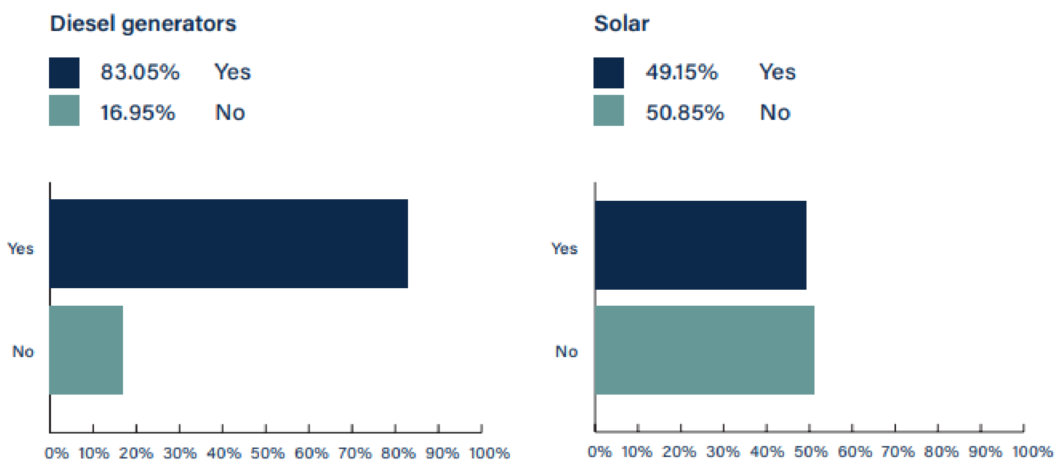

Figure 1: Property companies that have preventative measures implemented to combat load shedding. (Source SAPOA, 2023).

In the SAPOA Survey (2023), 44.07% of commercial property investors registered with the association reported that load shedding is having a serious impact on their businesses, while 25.42% reported the impact of load shedding as a "moderate impact," and 28.81% reported the impact of load shedding as "very serious, affecting business viability and sustainability." Only 1.69% of the survey respondents reported that outages have had "no impact" on their businesses. Indeed, the survey's outcome showed that property investors are incurring extra expenses directly and indirectly linked to the power outages. 7.74% reported monthly costs of more than R10 million due to load shedding. These costs include additional fuel expenses to operate generators, lost labour productivity, and damage to machinery.

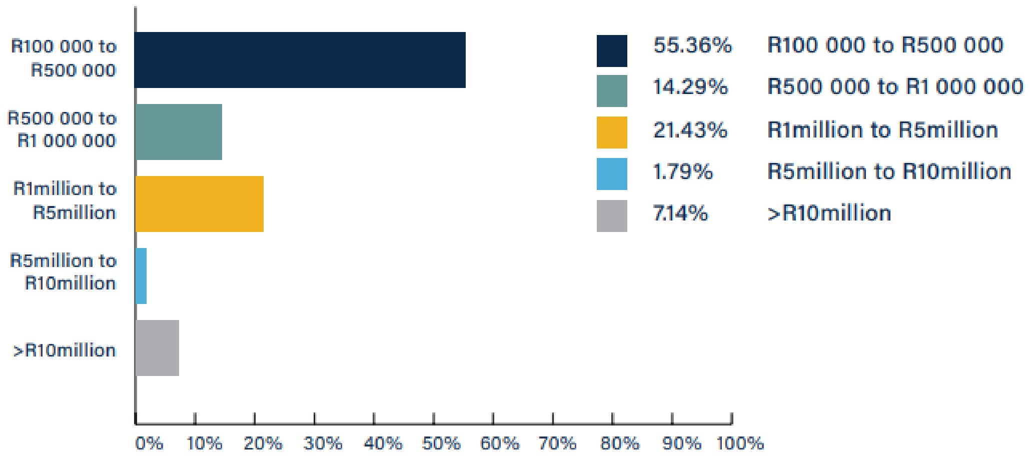

Figure 2: Estimated indirect load shedding costs per month. (Source: SAPOA, 2023)

Two survey questions were posed to SAPOA property investor members: "What is the impact on service delivery in general?" and "What actions has your organization taken to mitigate the impact of load shedding?" The respondents' top three answers for the first question were as follows:

- 57.69% reported that load shedding resulted in heavy traffic on the roads, thus impacting their meetings and scheduled appointments.
- 63.46% reported that load shedding forced companies to spend excessive capital on infrastructure to minimize its impact.
- 65.38% reported that load shedding caused damage to business equipment.

The respondents' top three answers for the second question were as follows:

- 53.85% of respondents have implemented office contingency plans such as flexible work hours and work-from-home arrangements.
- 71.15% of respondents have installed UPS systems in their organizations.
- 75% of respondents have installed generators in their organizations.

Based on the responses to the SAPOA Survey (2023), most property organizations have resorted to alternative power supplies to reduce the impact of load shedding. Organizations that solely rely on electricity for their business production are heavily impacted, leading to a loss of revenue. This can have a knock-on effect on the rental income of REITs, as tenants may struggle to meet their rental obligations. Furthermore, load shedding can cause delays in construction and maintenance projects, leading to higher cost overruns and delays in project completion (Coetzee and Els, 2016). As a result, some REITs have invested in alternative energy sources such as generators and batteries to minimise the effects of load shedding on their operations (Schoeman and Saunders, 2019). This has resulted in additional costs for REITs, which can impact their profitability and investors' returns.

In December 2022, South Africa experienced the longest uninterrupted streak of load shedding from Eskom, which was 19 days and 19 hours, or a total of 984 hours of blackouts (CSIR, 2022). This was followed by September 2022 which recorded 475 hours of uninterrupted streaks of load shedding. According to Loewald (2023) in an economic analysis publication released by SARB, the country endured its most severe year of load shedding in 2022, enduring a staggering 3,776 hours of power outages, equivalent to approximately 157 days without consistent electricity. This figure represents a significant increase compared to the 2021 record of 1,153 hours (48 days) and the 844 hours (35 days) lost in 2020. Unfortunately, the burden of load shedding has persisted into 2023, with the nation already grappling with 2,434 hours, translating to 101 days of power outages, as of April 16th. In essence, this means that power interruptions have become a near-daily occurrence this year (Loewald, 2023).

This had a negative impact on South Africa's economic growth. In the fourth quarter of 2022, South Africa's economy contracted by 1.3% (Statistic SA, 2023). The South African National Treasury released a budget review report of the country's economic forecast for 2022, the country realised a 4.8% GDP growth in 2021 as compared to the projected rate of 5.1% at the time of the 2021 Medium Term Budget Policy Statement. The National Treasury projected real economic growth of 2.1 per cent in 2022 and this prediction was based on the expectation that the economy would return to pre-pandemic production levels. However, in 2022, the country experienced a real GDP growth decline of 2%. The African Economic Outlook 2023 report elaborated that the factors which implicated this low growth rate were the ongoing electricity shortages, flooding in KwaZulu-Natal, and challenges in the transportation sector, together with the global economic downturn following Russia's invasion of Ukraine.

REITs have suffered the consequences of load shedding by either deploying capital to invest in alternative energy sources to maintain operations during outages or, for those that have not invested in alternative energy, lost money due to their inability unable to operate during those periods.

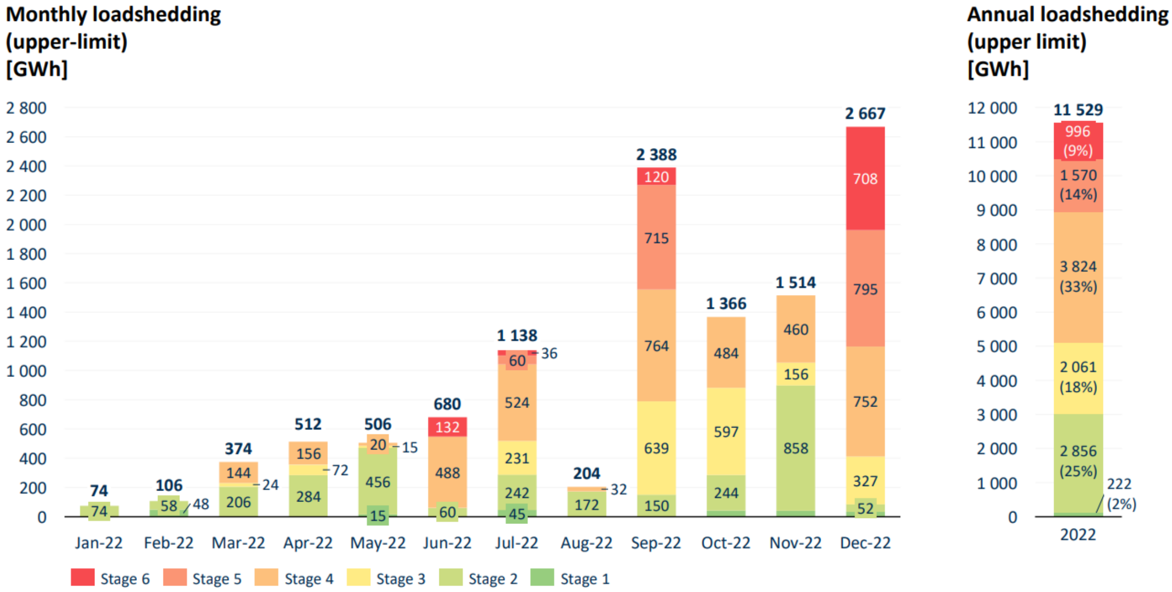

Figure 3: Monthly load shedding distributed in 2022. (Source: CSIR Report, 2022)

Figure 3 shows that December 2022 was the highest month in terms of load shedding. Stage 6 was first implemented in June 2022. Load shedding was intensified from September 2022 until December 2022.

Figure 3 shows South Africa's GDP performance for 2022. The country's highest GDP was 1.8% in the third quarter followed by the lowest GDP performance which was in quarter four with a 1.3% contraction. Figure 2 illustrates the 12-month performance of 29 SA REITs from 1 February 2022 to 31 January 2023. These 29 REITs are registered members of the SA REIT Association, which serves as the overarching representative body for South African REITs. The data presented in Figure 4 indicates that only 41.34% of the REITs achieved a positive outcome for the year. Among these, Octodec emerged as the highest performer with a 41.8% increase, while Rebosis A exhibited the poorest performance with a negative 70.4%.

In a podcast by Anderson (2023), the Head of Listed Property & Portfolio Manager at Merchant West highlighted the persistent challenges of load shedding in South Africa and the escalating global interest rates as the primary impediments affecting the performance of South African REITs. At the onset of 2023, the sector experienced a decline of just under 5%, underperforming both the South African equity and bond markets. Anderson further expounded that load shedding between stages 3 and 6 is significantly impacting investor sentiment towards South Africa in general, and the listed property sector in particular.

Anderson goes on to explain that although quantifying the full impact of load shedding across the REIT sector is complex due to varying power needs among different property types and tenants, it is evident that load shedding presents a substantial obstacle for South African REITs in 2023, likely resulting in a reduction of distribution growth by a few percentage points this year. While REITs can recover some costs associated with load shedding from their tenants, a considerable amount of capital expenditure is necessary to fully mitigate its impact in the long term. It is important to note that many companies in the sector have already made significant efforts to safeguard their tenants from the effects of load shedding, a fact that may not be fully recognized by the market. As a result, the average South African REIT continues to trade at a 30% discount to its net asset value.

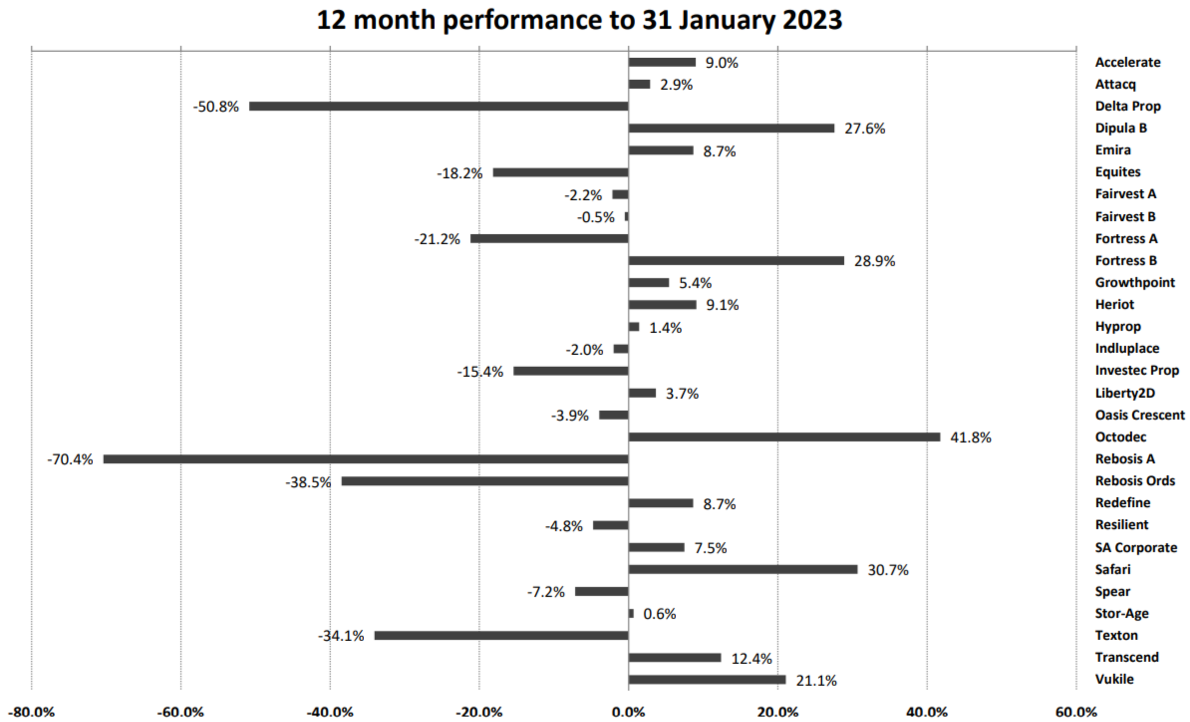

Figure 4: 12 month performance of 23 SA REITs from 1 February 2022 to 31 January 2023. (Source: SA REIT Association)

According to the South Africa Reserve Bank (SARB), load shedding was one of the contributing factors to the outcome of South Africa's GDP in the fourth quarter. The SARB has predicted that the country's economic growth for this year will be reduced by two percentage points due to load shedding. In addition, the SARB has warned that load shedding may cause a rise of up to 0.5 percentage points in headline inflation rate in 2023. This is due to the high operating expenses of running diesel generators, which are passed on to consumers, as well as the increased likelihood of waste and spoilage in food value chains, which could lead to potential supply shortages.

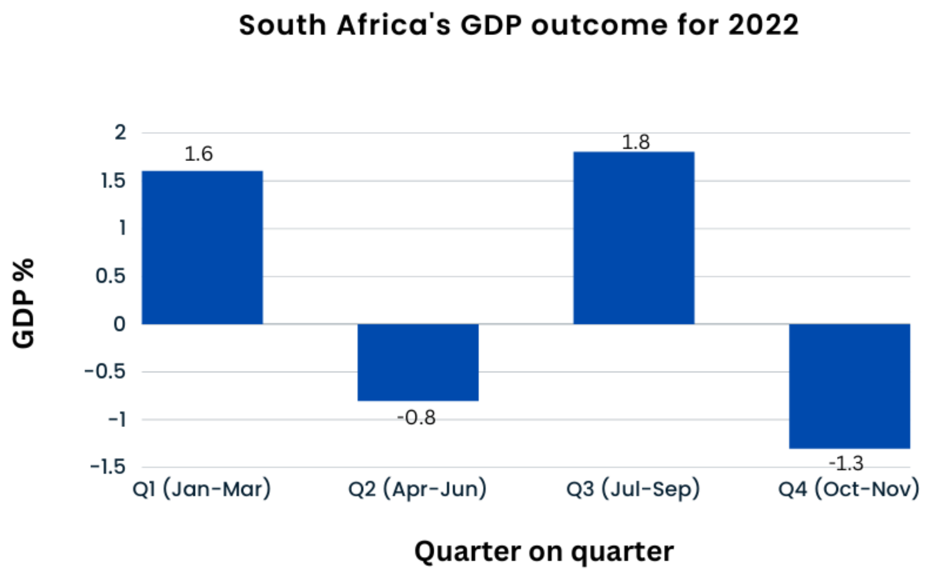

Figure 5: South Africa's quarterly GDP outcome in 2022 (Source: Stats SA, 2023)

1.1. Problem Statement

Load shedding first occurred in South Africa in 2007 and has become increasingly severe over the years, with frequent outages in 2022, due to electricity supply constraints where the demand for electricity exceeds the supply because of a lack of infrastructure to support the growing demand (Lenoke, 2017). On May 10th, 2023, Electricity Minister Kgosientsho Ramokgopa reported that load shedding resulted in the loss of more than 650,000 jobs in 2022, and this number is expected to increase further if the power crisis continues to persist. The Introduction section has explored the impact of load shedding on South Africa's economy.

Power shortages are not unique to South Africa, as many Sub-Saharan African countries have unstable power supplies (Cole et al., 2018). Other countries such as India (Siddiqui et al., 2015), Brazil and Paraguay (Matthewman & Byrd, 2013), and Germany (Growitsch et al., 2013) also face similar issues, with power outages resulting from a supply deficit. Montmasson-Clair (2016) highlights that a stable supply of energy is necessary for functioning economic, political, and social systems, as electricity is an enabler of socio-economic development. Most literature studying the relationship between electricity consumption and economic growth suggests a bidirectional relationship between the two. The increase in demand for electricity to support economic activity puts pressure on electricity suppliers to meet the demand, but South Africa's main electricity supplier, Eskom, does not have adequate infrastructure capacity to meet the growing demand. Thus, load shedding has become common.

The concept of REITs was first introduced in South Africa in 2013, following the enactment of the South African REITs tax regime, which allowed property companies to convert to REITs (JSE, 2020) (SA REIT Association, 2021). REITs in South Africa have grown significantly, attracting both domestic and international investors seeking stable income and diversification benefits from the property market (Kruger, 2017). Despite their potential as a stable investment vehicle, South African REITs have faced challenges in delivering consistent returns, particularly in recent years.

Issues affecting REIT performance in the South African market are the high level of market volatility and economic uncertainty, exacerbated by structural economic challenges such as low GDP growth, high unemployment rates, and political instability (Bonga-Bonga & Mwamba, 2018). In the February 2023 State of the Nation Address (SONA), President Cyril Ramaphosa acknowledged these persistent economic challenges, stating: "Our economy continues to face significant headwinds, with unemployment at unacceptably high levels and growth remaining subdued. The ongoing energy crisis has further constrained economic activity, undermining investor confidence and job creation." This statement highlights the difficult economic environment that has contributed to heightened market volatility and weakened investor confidence.

Furthermore, the South African REIT market has been affected by macroeconomic factors such as rising interest rates and inflation (Lenoke, 2017). For instance, in 2020, the South African property market saw significant declines in REIT performance due to the combined effects of the COVID-19 pandemic, national lockdowns, and macroeconomic instability (Iyer and Peydró, 2020). The issue of volatility within the South African REIT market not only reduces investor confidence but also raises concerns about the sector's long-term sustainability. The issue of underperformance is particularly concerning because REITs are often marketed as a reliable income-generating investment, especially in a low-interest-rate environment. However, the South African market has struggled to provide the expected levels of stability and growth, leading to diminished investor returns and reduced attractiveness of REITs as an asset class (Mhlanga & Mhlanga, 2021).

The South African REIT market is relatively small and less diversified compared to more established markets, such as those in the United States or Europe. This limited diversification reduces the ability of REITs to mitigate risks and sustain performance during periods of economic downturn, making the sector more vulnerable to localized economic shocks (Nguyen & Ming, 2019). One such shock is load shedding, which has significantly disrupted business operations and reduced demand for commercial and industrial properties. Naidoo (2023) highlights that load shedding has a devastating effect on various aspects of the South African economy, including industry shutdowns and a steep decline in productivity. These disruptions can lead to reduced demand for commercial spaces and increased vacancies, thereby impacting REIT revenues and performance. The purpose of this study is to determine the impact of load shedding on SA REIT returns, as well as the direction and magnitude of this impact. The initial intention of this study was to utilise data from the period 2014, which corresponds to the establishment of SA REITs in South Africa, through the end of 2022. However, Eskom Load Shedding data is only available for a 5-year period. Therefore, for this study, the analysed period will span from April 2019 to December 2023. A major focus of the study will be to examine the performance of REITs during prolonged power outages and their effect on returns. This is supported by available search research results, including the 2022 integrated reports by Spear REIT Limited and Fairvest Limited, which highlight their efforts to provide load shedding protection and the subsequent positive impact on their portfolios. Furthermore, analysis of the problem tree for the planning and implementation of the Department of Public Works and Infrastructure underscores the importance of assessing the performance of REITs during load shedding.

There have been numerous studies conducted on the performance of global REITs, including SA REITs. These studies date as far back as 1960, when REITs were first established in the USA. However, there have been no direct studies conducted to ascertain the impact of load shedding or power cuts on REIT returns. This study seeks to explore these possible linkages.

1.2. Research Questions

The key research questions for this study are:

1. How has load shedding impacted SA REIT returns historically and what is the predicted future forecast?
2. What is the impact, if any, of load shedding on REIT returns?

3. Through which channels do load shedding affect SA REITS returns?

1.3. Purpose and objectives of the study

The aim of the research is to assess the effects of load shedding on the performance of SA REITs by analysing its impact. The research will investigate the correlation between extended power outages and the performance of South African REITs, aiming to assess both the magnitude and direction of this relationship.

1. Determine if load shedding has an impact on SA REIT returns.
2. Determine what the future impact, if any, of load shedding on SA REIT returns will be.
3. Identify the channels through which load shedding may affect REIT returns.

1.4. Significance of the study

The primary objective of this research is to investigate whether load shedding affects the returns of SA REITs, particularly during extended power outages. The study's findings will provide direct benefit to various stakeholders, such as REIT property fund companies, asset managers, debt funders, and investors. By quantifying the effect of load shedding on REIT returns, stakeholders will be better equipped to make informed decisions regarding this sector moving forward which can possibly lead to a positive outcome in the future. It is worth noting that there is a lack of academic research that consider an appropriate theoretical framework to the research problem, highlighting a gap in the existing knowledge. In addition, this research aims to contribute to the development of risk management best practices during load shedding periods, maintain returns and support regulators in formulating policies that promote a more stable and resilient property market for the REIT sector.

2. Literature Review

2.1. REIT Introduction

REITs were first implemented in the USA in 1960. Chan, Erickson & Wang (2002), Block (2012) and Fasanya & Adekoya (2022), state that the purpose of REIT markets is to allow individuals to invest in real estate portfolio through the purchase of shares in a management fund. REITs illuminate the burden of owning and managing the physical asset and this type of investment is also less capital extensive. REITs are an indirect investment in real estate. Fund managers strategically manage the portfolio to maximize shareholder wealth, they borrow debt and issue public traded shares. REITs predominately comprise of leased property and or portfolios of mortgages, both produce relatively stable and contractual cash flows (Toth & College, 1993). The property assets in the portfolio are income producing.

According to NAREIT (2022), there were a total of 893 listed REITs operating across the world as of December 2022, with a combined equity market capitalisation of US$72 trillion. The GDP of REIT countries and this region has increased considerably from $6.5 billion to nearly US$98 trillion in 2022 (NAREIT, 2022). REITs are present in 41 countries, including South Africa. The USA has the biggest REIT market globally, with 168 REITs listed on the New York Stock Exchange, with a combined market equity capitalisation of US$1.04 trillion as of 31 May 2023, according to NAREIT. Equity REITs and mortgage REITs are the two main types of REITs that own and operate income-producing real estate assets worldwide (Li & Orzano, 2020). Equity REITs are responsible for managing and owning real estate assets that generate rental income, whilst mortgage REITs extend loans directly to property owners or indirectly via buying mortgages or mortgage-linked securities, earning interest income from such investments (Li & Orzano, 2020). Overall, REIT markets are a significant contributor to the global economy, with widespread market capitalisation.

South Africa’s power energy crises began in 2007 and this due to Eskom’s struggles to meet the increasing demand for electricity. This is due to a combination of factors including aging of infrastructure and insufficient investment in new power plants, maintenance neglect, and a rapidly growing economy led to a supply-demand imbalance, prompting Eskom to implement load shedding as a means of preventing a nationwide blackout. The Public Servants Association of South Africa stated that South Africa is losing its competitive edge as an investment destination as the enthusiasm from potential investors decrease due to the country’s persistent energy crisis.

Chapter 1 provided an introduction and background to the study and this chapter will review the relevant literature to this study.

2.2. SA REIT Background

REITs in South Africa have significantly evolved since their introduction in 2013, aimed at attracting local and international investment in the property market while offering accessible entry with reduced capital requirements (JSE, 2020). Initially, the South African property market primarily relied on PLS and PUT, each governed by distinct statutory and tax frameworks (Kruger, 2017). PLS operated as companies and were subject to a 28% income tax rate, contrasting with PUTs, which as trusts taxed investors directly upon income distribution (Kubheka, 2019). These differences created inconsistencies and hindered international recognition.

The introduction of REITs helped to unify tax treatment across listed property entities, aligning South Africa's regulatory framework with international standards and improving the competitiveness of the local market (Naidoo, 2014). Following the adoption of the REIT structure, numerous PUTs and PLSs converted to REITs under the new regulatory framework (Boshoff & Bredell, 2013). Qualification required adherence to the JSE's REIT regulations, including distributing at least 75% of distributable profits to shareholders within four months of year-end and maintaining a property asset base exceeding R300 million (JSE, 2014).

SA REITs may adopt either corporate or trust structures and enjoy a favourable tax regime, paying a 28% tax rate on income and exempt from capital gains tax on property disposals (Ntuli & Akinsomi, 2017). This simplicity and tax advantage make REITs an attractive investment, facilitating global comparability and enhancing market transparency (Boshoff & Bredell, 2013).

Investors benefit from REITs' compliance with stringent JSE rules, ensuring stability through mandatory distribution of income and revenue derived predominantly from rental activities (Ijasan et al., 2021). This stability is crucial as REITs provide less cash-intensive investment opportunities compared to direct property ownership, thus diversifying investment portfolios effectively (Ijasan et al., 2021).

The resilience of South African REITs amid global economic fluctuations underscores their importance in diversified investment portfolios (Fasanya & Adekoya, 2022). With a significant market capitalization exceeding R389 billion among the top 20 REITs as of 2020, South African REITs play a pivotal role in the local financial landscape (JSE, 2020). Globally, South Africa ranks prominently in terms of REIT market size, reflecting the sector's maturity and investor confidence (EPRA, 2014). REITs continue to demonstrate enduring performance, consolidating their position as a preferred investment vehicle both domestically and internationally (Ntuli & Akinsomi, 2017).

South African REITs have transformed the local property market by providing efficient access for investors, aligning taxation with global standards, and contributing significantly to the country's financial sector stability. Their continued evolution and adherence to regulatory standards ensure their role as a cornerstone of diversified investment strategies.

2.3. SA REIT risk performance and diversification

Risk management is critical in SA REITs due to their exposure to property market fluctuations, tenant risks, and economic cycles. To mitigate these risks, effective strategies include thorough property due diligence and diversification across property types (e.g., retail, office, industrial), geographic locations, and tenant sectors (Ntuli & Akinsomi, 2017). This diversification helps spread risk, reducing vulnerability to issues affecting specific properties or sectors, and enhancing overall portfolio stability. Despite these risks, SA REITs have shown resilience and competitiveness, providing investors with steady dividend income supported by long-term leases that ensure predictable cash flows. Studies suggest that SA REITs have lower volatility compared to broader equity markets, making them attractive during economic downturns (Ijasan et al., 2021).

SA REITs offer substantial diversification benefits within investment portfolios. By investing in a wide array of properties across different sectors and locations, they reduce exposure to localized economic downturns or sector-specific challenges, thus spreading risk (Fasanya & Adekoya, 2022). Additionally, REITs enhance liquidity since they trade on stock exchanges, providing investors with a more liquid alternative to direct property ownership. However, challenges such as sensitivity to interest rates, regulatory changes, and macroeconomic fluctuations can impact performance. Therefore, strategic asset allocation, effective management, and active risk monitoring are essential to navigate these challenges (JSE, 2020).

Research by Ntuli and Akinsomi (2017) assessed the performance of SA REITs within mixed asset portfolios that included stocks, bonds, and Treasury bills. Their study found varying correlations between REITs and other asset classes, with strong correlations to listed property and bonds, moderate correlations to stocks, and minimal correlation with Treasury bills. These diversification benefits help reduce portfolio risk through exposure to assets with low inter-asset correlations. While high correlations between assets may offer higher returns, they also increase the risk that both assets could underperform simultaneously.

Further analysis by Ijasan et al. (2021) conducted a comparative analysis of SA REITs against 10 global REIT markets using coherence analysis and time series approaches. Their study reinforced the benefits of portfolio diversification in the short to intermediate term, advocating for strategies that incorporate high and intermediate frequency trading to optimize risk-adjusted returns. Their findings emphasized that while SA REITs exhibit little correlation with global REITs based on geographical and size variations, detailed analysis of evolving relationships is essential for informed investment decisions.

A study conducted by Kubheka in 2019 focused on utilising risk-adjusted return ratios such as the Sharpe ratio (Sharpe, 1966), Treynor index (cited by Sharpe (1966)), and Jensen's Alpha ratio (Jensen, 1968). This comprehensive analysis of 55 JSE-listed and delisted REITs provided insights into long-term performance trends and identified factors influencing risk-adjusted returns. The incorporation of these tools is appropriate as they allow for the use of risk-adjusted performance ratios in measuring the return on real estate investment funds and in discerning the performance of SA REITs.

Overall, SA REITs offer significant risk management and diversification benefits, making them a valuable component of mixed-asset portfolios. Their resilience, combined with effective risk-adjusted performance measurement tools, reinforces their role in providing stable returns while mitigating risk.

2.4. REIT performance in emerging markets

REITs in emerging markets differ in their regulatory frameworks, market maturity, and investor perceptions compared to developed markets. The adoption of REIT structures in these economies often aims to attract capital, enhance liquidity in real estate markets, and provide tax-efficient investment opportunities (Lee & Ling, 2017).

Emerging market REITs encompass a diverse array of countries, including Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Kuwait, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, and United Arab Emirates. South Africa ranks prominently as the second-largest REIT market in emerging economies, following Mexico (MSCI, 2023). The size weighting of the emerging markets REITs according to the MSCI Emerging Markets IM Core REITs Index (2023) shows Mexico at 39.14%, South Africa at 25.73%, India at 10.08% Malaysia 6.84% South Korea 6.12% and other make up 12.08%.

The risk management strategies employed by REITs in emerging markets vary based on local economic conditions, regulatory environments, and sector-specific challenges. Studies often analyze the impact of market volatility, interest rate changes, and regulatory reforms on REIT performance (Kim & Kim, 2018). Chiang and Liu (2020) studied the performance of Asian REITs across different market conditions, highlighting their resilience during economic downturns and their role in diversified investment portfolios.

Investor preferences in emerging market REITs often reflect a balance between income stability and growth potential. According to Su, Zhang, & Liu (2019), while these markets offer higher yields compared to developed markets, they also present higher risk profiles due to currency fluctuations, political instability, and less mature property markets. Tang et al (2018) explore regional differences in REIT performance within emerging markets, emphasizing the importance of local market conditions, regulatory frameworks, and economic policies in shaping REIT outcomes.

South Africa, with its substantial share of the emerging market REIT sector, has become a key player, second only to Mexico. Its REIT market has shown resilience and competitiveness in the global REIT landscape, driven by robust regulatory standards and a mature property sector. The diversified nature of South Africa’s REITs, combined with favorable tax regimes and strong market liquidity, makes it an attractive destination for both local and international investors.

REITs in emerging markets, including South Africa, provide substantial growth opportunities but require careful risk management due to their higher volatility and exposure to economic and political risks. Understanding the regional factors that drive performance, such as regulatory frameworks and economic policies, is essential for investors seeking to capitalize on these opportunities.

2.4.1. Nigeria Market Landscape

Nigeria's REIT market, established in 2007, represents the second-largest REIT market in Africa after South Africa. As of September 2022, the Nigerian REIT sector had a market capitalization of US$91.3 million, with three listed REIT companies (Mixta Africa, 2022). Despite its relatively small size, the market has shown potential for growth and offers investment opportunities that appeal to both local and foreign investors.

A study by Dabara (2021) assessed the risk-adjusted performance of Nigerian REITs compared to stocks and bonds. The findings revealed that Nigerian REITs outperformed stocks in terms of risk-adjusted returns but lagged behind bonds. This conclusion was drawn based on the return–risk ratio, coefficient of variation, and Sharpe ratio, which measured the returns relative to risk for the three asset classes. Nigerian REITs demonstrated lower volatility and better returns than stocks, making them a more stable investment in this context. However, bonds remained the superior option due to their lower risk profile and relatively higher returns.

Dabara also compared the regulatory frameworks of Nigerian REITs with those of South African REITs. South African REITs benefit from a more robust regulatory environment, with mandatory risk monitoring committees and stricter regulations on debt profiles. Dabara recommended that Nigeria adopt innovative regulatory frameworks similar to those of Belgium, where legislative changes introduced social dimensions and institutional involvement, leading to increased efficiency and attractiveness of Belgian REITs (Marzuki & Newell, 2019).

The comparison between Nigerian and South African REITs highlights the need for Nigeria to enhance its regulatory structure to improve market confidence and performance. Table 1 below outlines key differences between the regulatory frameworks of Nigerian and South African REITs.

Regulatory requirements	Nigerian REIT	SA REIT
Management strategy	Internal management	Internal and external management
Minimum required capitalisation	US$5 million	$19.7million
Overseas investments	no international investors	international investors
50/50 rule of ownership	Applicable	Not applicable
Number of unit holders	Minimum of 100	No restriction
Mandatory risk monitoring committee	Not mandatory	Mandatory
Debt profile	Not applicable	Below 60% of gross asset value
Size of market capitalisation	US$136m	US$22bn

Table 1: Comparative Regulatory Structures of Nigerian and South African REITs
Source: Dabara (2021)

Dabara's recommendations underscore the importance of improving Nigeria's REIT regulations to boost investor confidence and market performance. Strengthening the regulatory framework, particularly in areas like debt management and risk monitoring, would align Nigerian REITs with global best practices and make them more attractive to both domestic and international investors.

Nigeria's REIT market, though smaller than South Africa's, shows potential for growth. However, the regulatory structure requires enhancements to ensure long-term sustainability and investor confidence. Adopting innovative and robust regulatory measures, as seen in South Africa and Belgium, could enhance the overall performance of Nigerian REITs.

2.4.2. Hong Kong and Asian Market

The Asian REIT market has grown significantly since its inception, with 138 Asian REITs boasting a total market capitalization of over $118 billion, accounting for 12% of the global REIT market. The establishment of REITs in Asia began in Japan in 2001, followed by other countries such as Singapore, Hong Kong, South Korea, Taiwan, and Malaysia. According to Bothra (2014), the Asian REIT market, valued at US$7 trillion, represented approximately 25% of the global REIT market at that time. Bothra also projected that the Asian REIT market would expand to US$17 trillion by 2020, constituting 35% of the global market, driven largely by the rapid growth in emerging real estate markets across Asia.

A notable player in the Asian REIT market is Hong Kong, where the REIT market was established in 2003. The first traded REIT on the Hong Kong Stock Exchange was LINK REIT, which is currently the largest listed REIT in Asia. Established by the Hong Kong government through the Hong Kong Housing Authority, LINK REIT's success is indicative of the growth potential in Asian REITs (He & Stevenson, 2020). According to the EPRA's 2023 Emerging Market Report, China's REIT market index was valued at EUR 44.8 billion at the end of June 2023, reflecting China's growing prominence in the sector.

The performance of REITs in Asia has been the subject of various studies. Mohamad and Zolkifli (2014) examined the determinants of REIT performance in the Asian market, using net asset value (NAV) and return as performance proxies, and risk, dividend yield, net income, and size as determinant variables. Their study utilized correlations and multiple regression analysis, providing evidence of associations between NAV, return, and these variables, highlighting the importance of these factors in influencing REIT performance.

Asia's REIT markets have benefited from favourable macroeconomic conditions and government involvement. Ooi et al. (2006) analysed the growth of REIT markets in Asia, emphasizing the role of government policies in driving REIT development. Regulatory changes and deregulation were found to be key stimulants for growth, encouraging investment and promoting the success of REITs across the region. As a result, the REIT sector in Asia has grown exponentially over the past decade, with China's economy outperforming many developed economies, further enhancing the attractiveness of the Asian REIT market.

Overall, the Asian REIT market continues to demonstrate rapid growth, driven by strong government support, favourable regulatory environments, and the growing real estate sector. REITs in Asia offer investors exposure to dynamic markets, combining growth potential with income stability. Despite regional differences in regulatory frameworks and market conditions, the REIT market in Asia remains a crucial part of the global REIT landscape.

2.5. Factors that impacted REITs performance

REITs have been subjected to various global economic crises, including the US stock market crash, the Financial Crisis of 2007-2008, and the Covid-19 pandemic. This section studies global economic crises notably US stock market crash, the Financial Crisis and Covid-19 pandemic to discern their impact on REIT performance. The literature review will help unveil the resilience of real estate investments amidst turbulent times.

2.5.1. Stock Market Crash of 1987

The US stock market crash of 1987, known as Black Monday, saw the Dow Jones Industrial Average plummet by 22.6% in a single day, triggering panic selling and widespread investor uncertainty. Various factors contributed to the crash, including the overvaluation of stocks, rising interest rates, and the proliferation of computerized trading strategies exacerbating market volatility (Shiller, 1989).

Stocks across various sectors experienced sharp declines during the crash. Research by Poterba & Summers (1988) analysed the performance of individual stocks and found that high-flying growth stocks, particularly in technology and financial sectors, suffered the most significant losses. The volatility index surged, indicating heightened market fear and uncertainty among investors (Engle & Ng, 1993). This crash had significant implications for REITs. During this period, REITs demonstrated their resilience by providing stable income streams and serving as a hedge against stock market volatility, providing investors with a consistent source of income. (Brounen, 2003). Research suggests that while REITs experienced short-term declines in market value, their underlying real estate assets continued to generate steady rental income, buffering investors from the full impact of equity market downturns (Hartzell & Hekman, 1999). REITs served as a hedge against stock market volatility during this period.

Hartzell and Hekman (1999) observed that while REITs did face short-term declines in market value following the crash, their underlying properties continued to generate steady rental income. This income stability was crucial in buffering investors from the full impact of the equity market downturns. According to Gyourko & Keim (1992), REITs are essential components of diversified investment portfolios.

Despite the severe downturn, stocks began to recover relatively quickly in the months following Black Monday. Studies by Fama & French (1988) and Schwert (1990) examined the recovery patterns and highlighted the resilience of the stock market over the long term. The crash prompted regulatory and structural reforms aimed at enhancing market stability and investor protection. The introduction of circuit breakers and improved risk management practices helped mitigate future market downturns (Zimmerman, 1990). Scholars such as Shiller (1990) emphasized the need for systemic risk management and the importance of understanding market psychology in preventing future crises.

2.5.2. Global Financial Crises

The global financial crises (GFC) was a period of extreme stress in global financial markets and banking systems between mid-2007 and late 2009. The GFC was triggered by a combination of factors, with key contributors including the housing bubble burst in the United States, subprime mortgage lending practices, and the widespread securitization of subprime mortgages. The interconnectedness of global financial markets exacerbated the crisis, as the impact spread to banks and financial institutions worldwide (Turner, 2023). The GFC highlighted vulnerabilities in financial markets globally, impacting REITs through tightened credit markets, reduced property values, and declining occupancy rates. Studies indicate that REITs with stronger balance sheets and diversified portfolios fared better during this period compared to those heavily reliant on debt and specific property sectors (Liang & McIntosh, 2013). Government interventions, such as monetary easing and fiscal stimulus, supported real estate markets and facilitated REIT recovery post-crisis (Linneman & Hartzell, 1995).

In a research study conducted in 2009 by Newell and Peng, they examined the performance of Australian REITs during the GFC. They observed that Australian REITs demonstrated underperformance, heightened risk, and a diminished realization of portfolio diversification benefits amid the global financial crisis. Chiang, et al (2011) reported findings consistent with those of Newell and Peng. According to their research, REITs in Taiwan, Hong Kong, Singapore and Japan REITs (the 4 Asian markets) experienced an increase in risk following the GFC. Their empirical results suggest that Asian REITs may not provide the same defensive attributes during financial turmoil as they do in stable market conditions, rendering them less effective as a shelter from crises. The research implies that while investors might find value in including the four Asian REITs in their portfolios during periods of market stability, they could face significant losses during market crises due to the interconnectedness between REITs and stock markets.

2.5.3. Covid-19

In 2020, the World Health Organization implemented guidelines aimed at containing the spread of the coronavirus, including social distancing measures, which were widely adopted by countries globally. As a result, many businesses struggled to meet their rent obligations due to reduced revenues or income disruptions caused by the pandemic's economic fallout (Ahn et al., 2023).

Akinsomi (2020) conducted an analysis of REIT performance amidst the Covid-19 pandemic, assessing its impact on the real estate industry. Lockdowns and social distancing measures significantly reduced the use of commercial spaces such as offices, retail stores, and hospitality venues. This downturn adversely affected REITs, leading to issues in rent collection, profit distribution, and debt serviceability due to diminished cash flows. Akinsomi specifically studied US REIT asset returns from March to April 2020, comparing them to returns from the previous year. The retail and lodging sectors experienced substantial declines, with returns dropping by 48.75% and 51.31%, respectively. Reduced foot traffic led to fewer visits to shopping malls, prompting some landlords to offer rent concessions. Concurrently, e-commerce surged by 30.7% as consumers shifted towards online shopping. Moreover, remote work policies necessitated by movement restrictions led to increased vacancies in office properties and a rise in virtual meetings.

In response to these challenges, some REITs diversified their portfolios into resilient sectors such as logistics and healthcare, which experienced heightened demand during the pandemic (Ghosh & Zheng, 2021). This strategic diversification underscored the importance of balancing portfolio risk to mitigate pandemic-related disruptions.

Government interventions, including rent relief programs and fiscal measures, played a crucial role in alleviating immediate financial pressures on REITs (Iyer & Peydró, 2020). These initiatives provided temporary relief and supported the stability of the real estate market amidst unprecedented economic uncertainties.

Cai and Xu (2022) conducted a study comparing the net impact of Covid-19 to that of the 2008 GFC by utilizing the Fama-French model for REIT returns, focusing specifically on equity REITs. Their research revealed that the implementation of social distancing measures during Covid-19 facilitated remote working, a phenomenon absents during the GFC. Consequently, this led to a surge in e-commerce, driving demand for storage, distribution, and shipping services due to the increased popularity of online shopping. Notably, the findings indicated that during the GFC, the net impacts of recessions on office and residential REIT returns were negative and statistically significant, while being positive for industrial and retail REIT returns. In contrast, the impact of Covid-19 on industrial REIT returns, as well as office and residential, was unexpectedly positive. This unanticipated outcome could be attributed to existing office and residential leases, the percentage rent clause for commercial properties, and the grace period for residential properties during the COVID-19 pandemic.

2.6. Equity REIT Return

Rental income serves as the lifeblood of REITs, shaping their capacity to generate returns for investors through dividend payments. Another important element in REITs is the net asset value of a portfolio which determines the capitals gained throughout the holding period, thus indicating the performance of a REIT financial health and performance of an investment. According to Chacon (2021), profitability can be enhanced by increasing revenue in REITs. One way to achieve this is through high tenant concentration, which contributes to operational efficiency.

In a study conducted by Olanrele (2014), a regression analysis was employed to assess the performance of REITs. The research followed a quantitative approach and focused on the performance of one REITs named, AMFIRST REIT, a registered entity on the board of Bursa Malaysia Securities Commission's market, over a period of six years spanning from 2007 to 2013.The study conducted by Olanrele was of a micro-level nature, concentrating on a single company, and therefore cannot be extrapolated to represent the aggregate performance of Malaysia's National REITs. The chosen dependent variable was dividend, while the predictor variables encompassed the net asset value, capitalization, asset value, net income, and leverage.

Notably, the findings revealed an intriguing relationship between net income and dividend. During the years 2007 to 2009, the dividend exhibited an increase in tandem with the rise in income. Conversely, in 2010 and 2011, the dividend rose despite a decline in income attributable to the global financial crises of 2007/2008. The results of the regression analysis also yielded standardized beta values for the determinant factor variables.

Chan, et al (1990) focused on appraisal-based return whereby they analysed monthly return on equity REITs traded on major stock exchanges over 1973 to 1987 using the Arbitrage Pricing Model and Capital Asset Pricing Model. The macroeconomics variable included expected inflation rate, unexpected inflation rate, industrial production growth, low grade corporate bonds and long-term treasury bonds. Chan et al (1990) concluded that real estate serves as a good hedge against inflation rate but not against unexpected inflation rate.

Numerous empirical studies conducted throughout history on stock returns and inflation rate consistently demonstrate a negative relationship between the two variables. (Fama and Schwert, 1977, Geske and Roll, 1983, Gyourko and Linneman, 1988 and Hess and Lee, 1999). REITs are recognised for their ability to serve as a hedge against inflation rate. This characteristic stems from the unique structure of REITs, which typically own and operate income-generating real estate assets such as commercial properties, residential complexes, and infrastructure. In times of inflation rate, the value of tangible assets like real estate tends to appreciate, providing a natural buffer against the eroding effects of rising prices. Moreover, REITs often have the flexibility to adjust rental rates in response to inflation rate, allowing them to generate increased income and maintain the purchasing power of their returns. As investors seek avenues to preserve the value of their investments during inflationary periods, the stable and appreciating nature of real estate within the REIT framework makes them an attractive option for those looking to hedge against the impact of inflation rate.

Yobaccio et al (1995) examined the ability of REITs to hedge against expected and unexpected inflation rate over a period of 1972 to 1992 and the results indicated that REITs provide some hedging capability against expected inflation rate but act as perverse hedges against unexpected inflation rate. Park, et al (1990) investigated the relationship between REITs and anticipated inflation rate using the methodology developed by Fama and Schwert (1977) their findings suggest that for the most part REITS, like stocks are perverse inflation rate hedges, they are indistinguishable from stocks in terms of hedging characteristics.

2.7. Impact of load shedding

Load shedding affects households by disrupting daily routines and essential services. Research by Khan & Mahmood (2017) indicates that communities in load shedding-prone areas face challenges in accessing reliable electricity for cooking, heating, and lighting. Vulnerable populations, including the elderly and those with health conditions, are particularly affected by power outages that compromise medical equipment and climate control (Bhattacharyya & Timilsina, 2010). In terms of education, students and teachers face disruptions in learning due to lack of electricity in schools and limited access to digital resources during load shedding hours (Eberhard et al., 2017).

Energy is key driver economic growth in emerging countries (Oluwasuji et al, 2019, Nweke and Ngwuta, 2016 and Timilsina et al, 2018). Load shedding, a common occurrence in many emerging countries, refers to the deliberate reduction or interruption of electricity supply to balance electricity demand with available power. This practice is driven by the challenges of insufficient infrastructure, rising energy demands, and strained resources (Nduhuura et al, 2020, Fabiyi et al (2015) and Sakrani et al, 2012). The impact of load shedding on emerging countries is multifaceted, affecting various sectors such as industry, healthcare, and education. In industries, often small businesses, face disruptions in production schedules, leading to economic setbacks, while larger companies incur additional expenses on generators and diesel (Timilsina et al., 2018). Studies by the Energy Research Center (2019) and Khan & Mahmood (2017) indicate that prolonged periods of load shedding result in reduced productivity and output losses in key sectors such as manufacturing, mining, and services. The lack of consistent electricity supply poses hurdles for technological advancements and overall economic growth. Therefore, load shedding presents formidable challenges for emerging countries, hindering their progress and potential for development (Anderson and Dalgaard, 2013).

The uncertainty caused by load shedding undermines investor confidence and deters foreign direct investment (FDI). Research by the World Bank (2020) highlights those countries experiencing frequent power outages face challenges in attracting and retaining investments.

2.7.1. Nepal

Nepal is a country that faced a decade of load shedding between 2007 and 2017 due to very low river discharge in the dry season, poor electricity management and increasing demand for electricity (Bhattarai et al., 2015 and Timilsina and Steinbuks, 2021). The Nepal Electricity Authority (NEA) implements load shedding schedules to manage electricity demand and supply imbalances, with daily outages lasting several hours, particularly during dry seasons when hydroelectric production is limited (Shrestha & Shakya, 2017). Timilsina et al (2018) estimated that Nepel has lost a total of US$11 billion value of GDP in nine years between 2007 and 2016 using a computable general equilibrium model. Acharya & Bhandari (2018) and Bhattarai et al. (2015) highlight those industries, particularly manufacturing and tourism, face significant production losses and increased operational costs due to reliance on diesel generators during power outages. Small and medium enterprises (SMEs) are particularly vulnerable, as they struggle to maintain consistent production schedules and meet customer demands. Walsh et al (2021) estimated the South African economy has lost nearly R35 billion (nearly $1.87 billion) over 12 years from 2007 to 2019.

The situation in Nepal regarding electricity has improved due to factors such as increased domestic supply, investments in hydropower projects, infrastructure upgrades, and efforts to diversify energy sources through renewable energy development (Shrestha et al., 2019). Policy interventions aim to enhance energy security, reduce dependency on imported electricity, and promote sustainable energy solutions to mitigate the impact of load shedding on economic growth and social welfare. Community resilience efforts, such as community-managed microgrids and energy conservation initiatives, are also underway to reduce dependence on the national grid and improve local energy resilience, as highlighted by Maharjan & Joshi (2016) and Shrestha et al. (2019).

2.7.2. Nigeria

Nigeria's load shedding has been ongoing for numerous years. According to Nweke and Ngwuta (2016) The continuous power shortages cause substantial economic losses, discomfort, and inconvenience across industries. The root causes of Nigeria's electricity challenges include insufficient generation capacity, transmission losses, and infrastructural deficiencies within the power sector (Okafor et al., 2018; Ibrahim et al., 2020). The national grid struggles to keep up with the escalating demand from industrial, commercial, and residential consumers, necessitating frequent load shedding schedules managed by the Transmission Company of Nigeria and distribution companies.

Okafor et al. (2018) conducted a study focused on the Enugu Electricity Distribution Company (EEDC), responsible for the Southeast geopolitical zone in Nigeria. Their research compared the costs incurred by consumers using private generators versus paying EEDC electricity bills. The findings revealed that the expenses associated with private generators were nearly double the costs of electricity provided by EEDC. Additionally, Onyishi et al. (2020) noted that EEDC could only supply approximately 10 hours of electricity daily to Enugu State, prompting recommendations for rotational load shedding as a strategy to manage demand and reduce reliance on costly alternative power sources.

Fabiyi et al. (2015) argue that Nigeria needs to adopt long-term solutions to address the issue of load shedding. Recommendations include upgrading aged equipment, combating corruption in the energy sector, and exploring alternative power sources such as solar and nuclear energy. Meanwhile, community resilience efforts, as highlighted by Okafor et al. (2018) and Ibrahim et al. (2020), involve local initiatives for energy conservation and the development of small-scale power generation projects aimed at reducing reliance on the national grid and enhancing energy resilience at the grassroots level.

Despite these efforts, the Nigerian government's policies and initiatives to mitigate load shedding, including investments in power infrastructure, privatization of the electricity sector, and promotion of renewable energy projects (Ibrahim et al., 2020; Ajie et al., 2019), have not been entirely effective in eliminating the problem.

2.8. Strategies to mitigate the impact of load shedding.

Investments in infrastructure play a crucial role in improving the capacity and reliability of electricity supply systems. Timilsina and Steinbuks (2021) highlight the significance of upgrading aging power plants, enhancing transmission and distribution networks, and expanding generation capacity to meet the increasing energy demands. These infrastructure upgrades are essential to reduce the frequency and impact of load shedding episodes, thereby supporting economic activities and enhancing overall productivity.

In response to frequent power outages, self-generation methods have become a prevalent strategy among businesses to mitigate the adverse effects of load shedding. Nurudeen et al. (2018) and Mahmud et al. (2019) note that firms equipped with backup power sources, such as generators, inverters, and solar systems, can sustain their operations during electricity interruptions. In contrast, businesses without backup energy sources often face disruptions and production losses during power outages, impacting their profitability and operational efficiency (Kupzig, 2020).

However, according to Nurudeen et al. (2018), the adaption of backup energy sources such as inverters, generators, and solar, among others, comes with a high cost, sometimes as much as three times the cost of publicly supplied electricity. Consequently, load shedding has increased operational expenses for REITs as they have to invest in alternative energy to maintain their standard operating levels.

A case study report from Technavio (2023) forecasts that the solar energy market in South Africa will experience a compound annual growth rate of 29.91% from 2022 to 2027. The report underscores the increasing government support for solar energy initiatives, which is a primary driver of market expansion. Given South Africa's abundant solar radiation and favorable geographical conditions, solar energy stands out as the most accessible renewable resource in the country (Technavio, 2023).

Nkateko's research (2021) explores the integration of solar energy into the grid supply chain to mitigate the impact of load shedding. The study conducted an experiment installing photovoltaic panels, which provided consistent power of approximately 240 Watts for 2 hours uninterrupted at a residential site. Based on these findings, the research advocates for the widespread installation of four million similar photovoltaic units to help alleviate stage-one load shedding incidents.

Smart grid technologies play a crucial role in enhancing electricity distribution efficiency by enabling real-time monitoring and management (Kamgang et al., 2018). These technologies optimize energy usage and minimize disruptions, ensuring a more reliable power supply. Moreover, energy storage systems like batteries and flywheels provide backup power during outages, ensuring continuity for critical facilities such as hospitals and data centers (Clement-Nyns et al., 2010). Moji et al. (2022) proposes the use of grid-connected hybrid photovoltaic battery and diesel generator systems for commercial buildings in South Africa to reduce operational costs during scheduled grid load shedding. They highlight the cost-effectiveness of this hybrid system compared to relying solely on photovoltaic batteries.

Programs promoting energy efficiency across households, schools, and businesses can also significantly reduce overall electricity consumption (Marshall et al., 2014). These initiatives include educating consumers on energy-saving practices and upgrading appliances to more energy-efficient models. Additionally, community-managed microgrids and decentralized energy generation initiatives empower local communities to generate their own electricity, reducing reliance on centralized grids (Shrestha et al., 2019). These decentralized approaches contribute to greater energy resilience and less vulnerability to disruptions caused by load shedding events.

2.9. Theoretical perspectives

2.9.1. Asset Pricing Model

Investors observe price movements in the stock market to make informed decisions about buying or selling securities. Monitoring these fluctuations allows investors to assess market trends, identify potential opportunities, and manage risk in their investment portfolios. The Capital Asset Pricing Model (CAPM) is a financial model that establishes a relationship between the expected return on an investment and its systematic risk. CAPM was developed by in early 1960s, and its initial formulation is credited to Sharpe (1964), Lintner (1965), and Mossin (1966), provides a framework for calculating the expected return of an asset based on its systematic risk (beta) relative to the overall market. CAPM quickly gained prominence and became one of the primary models in finance to price an equity.

Beta is a measure of systematic risk in the CAPM model, specifically indicating the extent to which an asset's returns are expected to fluctuate in response to changes in the broader market. A beta value greater than 1 suggests higher volatility than the market, while a beta less than 1 indicates lower volatility (Rossi, 2016). Key features and implications of the CAPM include assumptions that investors hold a diversified portfolio containing all risky assets in proportion to their market values, comprising both risky and risk-free assets within the market portfolio (Sharpe, 1964; Lintner, 1965; Mossin, 1966). CAPM incorporates the risk-free rate, which represents the rate at which investors can borrow or lend money without assuming any risk, thus reflecting the time value of money (Sharpe, 1964). Moreover, CAPM focuses on systematic risk, emphasizing that this component of risk cannot be diversified away by holding a diversified portfolio, contrasting with total risk, which includes both systematic and unsystematic risk components (Sharpe, 1964). These key elements underpin CAPM's framework for estimating expected returns based on an asset's systematic risk relative to the market, influencing investment decisions and portfolio management strategies in financial markets.

Despite its foundational role in financial theory, the CAPM has faced substantial criticism and encountered limitations. One prominent critique is its assumption that investors are consistently rational and risk-averse, maintaining well-diversified portfolios to mitigate unsystematic risk (Fama & French, 1992). However, in practice, investor behaviour can be influenced by factors not accounted for in CAPM, challenging the model's assumptions. Moreover, CAPM heavily relies on historical data to estimate beta coefficients, which gauge an asset's systematic risk relative to the market. This historical reliance may not always accurately forecast future market conditions, particularly during periods of market volatility or structural changes (Fama & French, 1993). Empirical research has also demonstrated that CAPM often fails to fully capture all factors influencing asset returns, such as size and value effects. As a response, more sophisticated models have been developed, including the Arbitrage Pricing Theory (APT) introduced by Ross (1976), the Fama-French Three-Factor Model (Fama & French, 1992), and the Carhart Four-Factor Model (Carhart, 1997). These frameworks enhance asset pricing theories by incorporating additional factors, providing a more nuanced understanding of financial market dynamics and addressing some of the limitations of CAPM.

Ross introduced the APT in 1976 as a robust alternative to the CAPM, aiming to address its limitations. CAPM relies on a single systematic risk factor and assumes a linear relationship between expected return and risk, whereas APT embraces arbitrage opportunities where investors exploit market mispricing’s to prompt price adjustments until equilibrium is restored. APT is a multifactor model that acknowledges multiple systematic risk factors influencing asset returns, including macroeconomic variables such as interest rates, inflation, GDP growth, and industry-specific factors. This flexibility enhances APT's ability to capture the complexities of financial markets compared to CAPM's simplistic approach focused primarily on beta. However, practical challenges in identifying and measuring these risk factors have been noted, as highlighted in early empirical studies (Roll and Ross, 1980).

The research gaps identified in the CAPM include its failure to account for additional risk factors, such as liquidity, momentum, and other variables, which have been shown to influence asset returns. This limitation has spurred the development of multi-factor models to provide a more comprehensive explanation of asset pricing. Furthermore, the model's reliance on market efficiency and rational investor behaviour has been questioned, particularly in emerging markets where market inefficiencies and behavioural biases are more pronounced, as highlighted by Harvey (1995).

The foundational assumption of APT is that efficient markets quickly adjust asset prices to reflect all available information, thereby eliminating arbitrage opportunities. This principle underscores the model's reliance on rational investor behaviour seeking to maximize returns while minimizing risk. According to Chen et al. (1986), systematic risk factors encompass changes in fundamental macroeconomic and financial variables like interest rates, GDP, and consumer confidence, influencing asset returns across diverse economic conditions. Unlike CAPM, APT's multifactor framework accommodates these varied sources of risk, providing a comprehensive tool for understanding asset pricing dynamics in real-world financial markets.

Empirical applications of the APT have validated its efficacy across different asset classes and global markets. Research by Chen et al. (1986) expanded APT's applicability by identifying macroeconomic variables like industrial production, inflation, and interest rate spreads as significant determinants of stock returns. Their time-series regression analysis of U.S. equities revealed that these macroeconomic factors capture variations in returns that CAPM's single-factor model cannot explain. Importantly, while Chen et al. (1986) focused on macroeconomic variables, later studies (e.g., Fama & French, 1992; Carhart, 1997) integrated firm-specific factors like size, value, and momentum into multifactor models—further validating APT's flexibility and broader explanatory power compared to CAPM.

Anindita and Gupta (2017) applied the Arbitrage Pricing Theory (APT) to the Indian stock market, employing time series regression analysis to investigate the impact of five macroeconomic variables on stock returns. Using the Ordinary Least Squares (OLS) method on stocks listed on the Bombay Stock Exchange, their findings concluded that macroeconomic factors significantly affect stock market performance. The study highlighted the relevance of APT in explaining asset returns in emerging markets, where macroeconomic variables play a critical role. These developments underscore APT's contributing in advancing asset pricing theory and refining models to better reflect the complexities and nuances of financial markets.

Recent studies have also explored extensions and refinements of APT, including the incorporation of additional factors beyond the original framework proposed by Ross. While APT remains flexible and theoretically robust, its practical application faces challenges in identifying relevant risk factors. The model does not specify which factors to include, leading to subjectivity in factor selection. For example, Chen et al. (1986) identified factors such as industrial production, inflation, and interest rates as significant determinants of stock returns, but the choice of factors varies across studies.

Despite its theoretical appeal, APT has not fully replaced CAPM in practice due to its complexity and the lack of consensus on the appropriate factors to include. Models like the Fama-French Three-Factor Model (Fama and French, 1992) and subsequent multi-factor models have built upon CAPM and APT to better explain cross-sectional variations in asset returns, such as size, value, and momentum effects. Fama and French (1992) applied their model to the US stocks listed on the NYSE, AMEX, and NASDAQ, incorporating size (SMB) and value (HML) factors alongside the market risk premium. Their findings demonstrated that the three-factor model outperformed CAPM in explaining stock returns, particularly for small-cap and value stocks. While APT is less specific in its factor specification compared to the Fama-French model, APT provides a theoretical foundation for developing and testing multifactor models that can capture the complexities of asset pricing in real-world financial markets.

A critical gap in the literature is the limited application of the APT in emerging markets, particularly in the context of REITs. Most empirical studies predominantly focus on developed markets, leaving a gap in understanding how macroeconomic factors influence REIT performance in emerging economies. While APT accounts for multiple risk factors, the selection and measurement of these factors remain subjective, contributing to inconsistencies in its empirical applications. Additionally, previous studies have not explored other potential macroeconomic factors, such as political stability, commodity prices, or global market trends, which could also influence stock returns in emerging markets (Ali & Mustafa, 2020; Mwangi & Njuguna, 2021). Future research could explore how different sectors (e.g., banking, technology, real estate) respond to macroeconomic shocks. The absence of a standardized set of factors highlights the need for further research to identify universally relevant factors, especially in emerging markets. Moreover, APT's reliance on market efficiency has been questioned, particularly in markets characterized by limited liquidity and high information asymmetry, further emphasizing the need to refine the model's applicability across different market environments. Furthermore, many studies assume a static relationship between macroeconomic variables and stock returns.

2.9.2. The Autoregressive Distributed Lag (ARDL) model

The ARDL model, introduced by Pesaran et al. (2001), represents a widely employed econometric framework that combines elements of autoregressive modelling with distributed lag modelling to examine relationships between variables over time. This model is particularly valued in both macroeconomic and microeconomic research due to its capability to handle non-stationary data and provide robust estimates of both long-run and short-run relationships. Recent studies suggest that the ARDL approach to cointegration is superior to other traditional methods, including those proposed by Engle and Granger (1987) and Johansen (1991), due to its flexibility in accommodating variables of different integration orders—I(0), I(1), or a mix of both (Pesaran et al., 2001).

The ARDL model's strength lies in its ability to estimate both short-run and long-run dynamics without requiring the variables to be fully stationary, which simplifies the analysis and reduces the risk of model misspecification. This is particularly relevant in financial studies, where variables often exhibit long-term relationships but fluctuate in the short term it makes it particularly suitable for examining the dynamic interplay between variables in economic and financial studies. It has methodological flexibility and robustness, especially in small sample sizes. However, despite its advantages, the ARDL model has some limitations. One critique of the ARDL approach is its sensitivity to model specification, particularly with regards to lag length and the inclusion of potential explanatory variables. As a result, researchers must exercise caution when selecting lag structures and validating results to avoid spurious conclusions.

This study adopts the ARDL methodology for cointegration, as introduced by Pesaran and Shin (1995) and further developed by Pesaran et al. (2001). The ARDL approach is preferred due to its flexibility, as it can be applied regardless of whether the regressors are entirely I(0), I(1), or a mix of both with cointegration. The key statistic in this method is the Wald (or F-statistic), which is used within a generalized Dickey-Fuller framework to assess the significance of lagged levels of variables in a conditional unrestricted equilibrium error correction model (Pesaran et al., 2001). Additionally, the ARDL approach is favoured for its robustness and superior performance in small sample sizes, which is particularly relevant for this study.

Empirical applications of the ARDL model span across various economic and social sciences disciplines, particularly in macroeconomics and finance. ARDL models have been extensively applied to explore the impacts of fiscal policies on economic growth, the interplay between inflation and economic activity, and the dynamics of exchange rate adjustments. For instance, studies have utilized ARDL to assess the efficacy of government spending and taxation policies in stimulating economic growth across diverse national and regional contexts.

In microeconomics and finance, the ARDL model has been employed to analyse determinants of firm-level investment decisions, the relationship between financial development and economic growth, and the dynamics of stock market volatility. Researchers have leveraged ARDL to investigate how financial variables such as interest rates, credit availability, and investor sentiment influence firm profitability and market performance over time.

Methodologically, the ARDL model integrates autoregressive and distributed lag components, enabling researchers to capture both immediate shocks and their prolonged effects over subsequent periods. This feature makes it suitable for examining dynamic relationships where variables respond gradually to shocks and may exhibit both short-run fluctuations and long-run adjustments.

This is similarly to the research conducted by Khan et al (2019) where they scrutinised the asymmetric impact of oil prices on stock prices in Shanghai stock exchange using the asymmetric ARDL model to analyse annual data from 1990 to 2017. The results of study showed that cointegration exists between the oil prices and the stock returns. The data of the study was monthly data from 2005 to 2017 and the asymmetric ARDL model findings also confirmed that both in the long run and the short run increase in oil prices had a negative impact on the stock returns of Shanghai stock exchange while decrease in the oil prices has a positive impact on the stock returns. While the study provided valuable insights into asymmetric relationships, it did not explore the role of other macroeconomic variables, such as interest rates or exchange rates, which could influence stock prices.

Khan et al. (2021) empirically explored the impact of oil prices and macro-economic factors on stock market development in Pakistan using a novel dynamic ARDL model for annual time series data starting from 1985 to 2017. The sample focused on the Pakistan Stock Exchange, incorporating data on oil prices, remittances, foreign direct investment, and exchange rates. The results revealed that oil prices, remittance inflow and foreign direct investment had a positive effect on the development of the Pakistan stock market. However, the exchange rate had a negative effect on the Pakistan stock market. The study further suggested that the government, policy makers and the investors should estimate probable changes in oil prices, exchange rate, expected inflow of personal remittances and FDI in order to easily forecast the performance of stock exchange in Pakistan. The critique on the study is that it provided a comprehensive analysis of macroeconomic factors but did not account for potential structural breaks in the data, which could affect the robustness of the results.

Oamruzzaman and Wei (2018) examined the relationship between economic growth, financial innovation, and stock market development of Bangladesh, using data on GDP growth, financial innovation indices, and stock market indicators between 1980 and 2016. The method used was the ARDL lagged bounds testing approach. The findings showed the existence of a long-run association between financial innovation, stock market development, and economic growth. The findings supported the theory that market-based financial development and financial innovation in the financial system can spur economic development. However, the study is that it did not explore the potential endogeneity between financial innovation and economic growth, which could bias the results. Additionally, the focus on Bangladesh limits the generalizability of the findings to other emerging markets.

The empirical studies reviewed highlight the versatility of the ARDL model in analysing both macroeconomic and financial phenomena. However, they also reveal several limitations and gaps in the literature. First, many studies focus on macroeconomic applications, leaving a relative dearth of research on microeconomic and firm-level phenomena. Second, most ARDL-based studies assume symmetric relationships between variables, potentially overlooking asymmetric dynamics that could be captured using nonlinear ARDL frameworks. Finally, there is limited research on the application of ARDL models in emerging markets, where data limitations and structural transformations may pose unique challenges. Future research could address these gaps by incorporating nonlinear ARDL frameworks, conducting robustness checks for structural breaks, and employing instrumental variable techniques to account for endogeneity.

3. Research Methodology

3.1 Introduction

This study will adopt a positivist paradigm approach which interprets pure data as well as facts provided without the influence of human bias. It emphasizes the importance of facts and observable regularities and minimizes the influence of human bias (Alharahsheh & Pius, 2020). Observational data will be collected, and a correlation research methodology will be used. The data collection process will involve gathering primary data in the form of historical records and analysing it comparatively with current data. Secondary data, which will mainly consist of quantitative data, will also be collected for comparative purposes.

The ARDL time series methodology will be utilised to determine if there is a relationship between load shedding and the S&P South Africa REIT Index, the time series analysis will be employed to conduct this study. A secondary test will be conducted using the APT model to determine the relationship between two SA REIT portfolio returns (herein referred to as Portfolio A and Portfolio B), beta risk and lambda factor sensitivities of a portfolio in the South African environment. The APT model will consist of a time series regression estimation. A robustness test will also be conducted on both models to assess the reliability and stability of the results.

Load shedding in South Africa is primarily caused by increased electricity demand exceeding available supply from plants, compounded by aging infrastructure and inadequate maintenance practices (du Venage, 2020; Naidoo, 2023). While not a global phenomenon, it is recognized as a critical concern in South Africa, with Ruffini (2015) highlighting that a total blackout in the country would be catastrophic.

Once the sample data are collected, significance testing will be performed on the dataset. During the time series analysis, the significance of all findings will be evaluated using the probability value (P-value). In confirmatory research, the P-value is a key metric, where a null hypothesis is proposed and then either accepted or rejected. The null hypothesis is rejected when the P-value is equal to or below a specified threshold, indicating statistical significance (de Bragança Pereira et al., 1993). For this study, a 95% confidence level is used, meaning that significance will be recognized when the P-value is 0.05 or lower. Hypotheses will be developed for each variable based on this criterion:

Null hypothesis: load shedding does not impact SA REIT returns.

Alternative hypothesis: load shedding does impact SA REIT returns.

In the current study, this appears to be the first time research has been conducted to explore the effects of load shedding on REIT returns.

3.2. Method of Data Collection and Preparation

Data for this study will be sourced from secondary sources, including online databases such as the JSE and Eskom's publicly accessible online database for load shedding data. Various time series analyses will be conducted using a consistent set of macroeconomic and load shedding data to statistically investigate the relationship between REIT returns and load shedding. Financial performance and macroeconomic data will be gathered from Bloomberg, South African statistical websites, and directly from REIT websites.

The analysis will encompass monthly REIT data from April 2019 to December 2023 and the data will be collected at regular intervals. This selected timeframe is due to the fact that published load shedding data on the Eskom portal only covers a five-year period. Although the performance data for load shedding and REIT prices are publicly available on a daily basis, the frequency of the data will be aggregated to a monthly basis to mitigate the noise caused by excessive frequency points (García et al., 2013).

This study will analyse predictability using time series model which is a statistical technique used to analyse and forecast data that is collected over a period of time at regular intervals (Granger and Morris, 1976). It involves studying the patterns, trends, and dependencies within the data to make predictions about future values. The journal written by Granger and Morris (1976) highlights the need to identify causal relationships and dependencies among variables in time series analysis. Through Time series analysis one can understand the underlying causes of trends or systemic patterns over time. Time series forecasting is part of predictive analytics and can be used to predict future events based on past data (Athanasopoulos and Hyndman, 2018).

3.3. Frequency Conversion

Both the dependent and independent variables will be converted to monthly measurements to achieve unified timeline. The conversion of data to monthly intervals will be done using EViews which has a data converting tool, from one frequency to another.

3.3.1. High to Low Frequency Conversion

EViews will be used to convert variables from daily frequency to monthly frequency data using its built-in averaging method. Within this process, the "Mean" function will calculate average values within each monthly interval using a rolling sample approach. The aggregation method will be adjusted to suit the specific characteristics of the dataset, ensuring that daily fluctuations are smoothed out effectively. This conversion process aims to provide a monthly representation that accurately captures the essential trends present in the original daily data. Once the data is collected it will be cleaned to remove any missing values or outliers that could skew the analysis.

3.3.2. Low to High Frequency Conversion

Low-frequency quarterly data will be converted to high-frequency monthly data using a similar technique mentioned above. Once data is imported and the monthly series is established, the "Expand" feature in EViews, will be employed by aggregating the monthly data by summing them over corresponding quarterly periods as the expansion technique. This function allows for the interpolation of quarterly or yearly data points to monthly intervals by calculating the average value across each month within the quarter or year.

3.4. OLS Estimator Technique

The Ordinary Least Squares (OLS) estimator is a statistical method used in regression analysis to estimate the parameters of a linear regression model. It works by minimizing the sum of the squared differences between the observed values and the values predicted by the regression model (Gujarati, 2019; Greene, 2020). OLS is widely used due to its simplicity and efficiency in estimating the relationship between variables. In this study the following OLS assumptions will be tested for:

1. Independence of errors – which assumes that errors are uncorrelated with each other;

2. Homoscedasticity – meaning that the variance of the errors is constant across all levels of the independent variables;
3. Normally distributed errors – which assumes that the errors follow a normal distribution with a mean of zero.
4. Multicollinearity - refers to the situation in which two or more independent variables in a regression model are highly correlated with each other.

Adhering to these assumptions ensures that the OLS estimator produces reliable and valid results. Violation of these assumptions can lead to biased parameter estimates and incorrect inference in regression analysis (Brooks, 2019). When these assumptions are met, the OLS estimator is considered to possess Best Linear Unbiased Estimator.

3.4.1. Autocorrelation Function and Randomness/White Noise

Autocorrelation refers to the statistical measure of the degree to which a time series is correlated with its own past values. In other words, it examines the linear relationship between two observations at different time points within the same dataset (The Pennsylvania State University, 2018). The correlations of time-series data are commonly discussed using the term "lags," which signifies the number of regular intervals between two observations in time series (Frost, 2021). Autocorrelation in the residuals suggests that there might be some systematic pattern left unexplained by the model, which could impact the reliability of the model's estimates.

The autocorrelation function will be utilized to evaluate the randomness and stationarity of a time series, even in the presence of trends and seasonal patterns. To detect first-order autocorrelation, the Durbin-Watson test will be applied, using the Durbin-Watson statistic, denoted by d. This statistic is approximately equal to $2(1-r)$, where r represents the sample autocorrelation of the residuals. A value of $d=2$ suggests no autocorrelation. The statistic ranges between 0 and 4; if d is significantly less than 2, it indicates positive serial correlation. If serial correlation is detected, additional lags will be incorporated into the regression analysis to appropriately model the data.

The Breusch-Godfrey LM test will be conducted in order to test for higher-order autocorrelation. The Breusch-Godfrey LM test

The results will be hypothesised as follows:

H0: There is no autocorrelation in the residuals up to a certain lag order.

H1: Autocorrelation is present.

3.4.2. Stationarity test/unit root

Determining the order of integration is crucial by confirming the stationarity of the series. The Augmented Dickey-Fuller (ADF) test will be used to conduct the stationarity test on the series. These tests will examine whether a unit root is present in a time series variable by estimating the stationary for the variables at the order of differencing zero, I(0). If non-stationarity exists then differencing of first and second order may be necessary to achieve stationarity; the series will be integrated of order one and two, I(1) and I(2) respectively.

The results will be hypothesised as follows:

H0: Not stationary

H1: Stationary

Hence, p-value should be smaller than 0.05 as the null hypothesis in these tests is that a unit root is present (implying non-stationarity), while the alternative hypothesis is that the series is stationary after differencing.

Although the ADF test is widely regarded as superior due to its popularity and extensive application, Nkoro and Uko (2016) warn that the ADF test's weakness lies in its failure to account for potential autocorrelation in the error process. When the error term is autocorrelated, the Ordinary Least Square estimates of the equations and their variants become inefficient. Dejong et al (1992), (Harris, 2003), Pahlavani (2005) and Shahbaz, et al (2008) further state that for small sample data set, the ADF tests seem to over-reject the null hypotheses when it is true and accept it when it is false. Nkoro and Uko (2016) and Dereli (2019) recommend the use of the Phillips-Perron (PP) test, developed by Phillips and Perron in 1988, as it is a common test for stationarity, and it addresses autocorrelation in the error term by testing if the variance of the time series is constant over time. However, according to Dejong et al. (1992), the PP test suffers from size distortion and low power when errors are autoregressively correlated. Given the small sample size for this research, the PP test may not be suitable for the model. On the contrary, research conducted by Hobijn et al. (2004) demonstrated that the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992) is a superior method for testing stationarity, particularly for small samples. Consequently, the KPSS test will be utilised in this research.

Similar to the ADF test, the KPSS test determines whether a time series is stationary around the mean or a linear trend. However, unlike the ADF test, if the p-value of the KPSS test is larger than the significance level of 0.05, then the series is deemed non-stationary. In contrast, for the ADF test, a smaller p-value implies stationarity. Thus, the hypotheses for the KPSS test are as follows:

H0: Stationary

H1: Not Stationary

3.4.3. Heteroscedasticity

Heteroscedasticity refers to the condition where the variance of the residuals varies across the range of observed values. In regression analysis, it implies that the variability of errors is not constant across different levels of the independent variables but rather varies systematically. Homoscedasticity, on the other hand, denotes a situation where the variance of residuals remains constant. Detecting heteroscedasticity can be achieved through tests such as the Breusch-Pagan LM test. This test evaluates the null hypothesis that heteroscedasticity exists against the alternative hypothesis of homoscedasticity. If the p-value from the test falls below the 5% significance level:

H0: presence of heteroscedasticity.

H1: presence of homoscedasticity

If heteroscedasticity is indeed detected, one corrective measure involves employing heteroscedasticity-robust standard errors. One widely used method for this purpose is White's test for robust standard errors, which can be applied to correct for heteroscedasticity in regression analysis.

3.4.4. Correlated Coefficient

The correlation between all the independent variables will be tested for using the Pearson correlation coefficient which is denoted by *r*. The formula for Pearson correlation coefficient between variables *x* and *y* is given by:

$$r = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\Sigma_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

- r is the correlation coefficient
- n is the number of observations
- x_i and y_i are the individual data points for variables *x* and *y*.
- $\bar{x}$ and $\bar{y}$ are the means of variables *x* and *y*.

Given the 10 independent variables correlation coefficients will be calculated for each pair of variables. There will be a total of 10*2=20 correlation coefficients and the number of observations will be monthly starting in 2014. EViews will be used to calculate correlation matrices efficiently to provide a comprehensive overview of the relationships between all pairs of variables.

r will give an indication if there is correlation or not as it always lies between -1 and 1 with negative values indicating a negative relationship and positive values indicating a positive relationship.

3.4.5. Multicollinearity

Another assumption of the OLS regression model is the absence of multicollinearity. Multicollinearity occurs when two or more independent variables are highly correlated with each other. To check for multicollinearity, one can examine the correlation matrix by calculating Pearson's Bivariate Correlation among all independent variables. Ideally, the correlation coefficients should be substantially less than 1. If multicollinearity is present, centering the data (subtracting the mean from each variable) might reduce multicollinearity caused by non-essential issues.

The Variance Inflation Rate Factor (VIF) will be used be used to detect multicollinearity. VIF measures the combined effect of the dependencies among the regressors on the variance of the regression coefficients. If VIF exceeds 10 it is an indication that multicollinearity exists.

There are several techniques to diagnose multicollinearity, Paul (2014) and Kim (2019) highlight ways to remedy multicollinearity which include:

1. Variable elimination – Removing one or more independent variables, known as variable elimination, can help reduce multicollinearity. However, this approach may not always be ideal, particularly if the excluded variables significantly explain the dependent variable. Excluding key variables can lead to misleading outcomes in regression analysis, causing biased estimates and potentially introducing new issues beyond multicollinearity. This process needs to be managed carefully, such as by removing one variable at a time rather than all correlated variables at once.

2. Use additional Data - Increasing the size of the sample may help alleviate multicollinearity issues. This is because larger samples provide more data points, which can lead to more accurate estimation of the regression coefficients and reduce the impact of correlation between variables. Expanding the sample size reduces the standard errors of regression coefficients. Standard errors indicate the accuracy of the estimates, and larger sample sizes generally lead to smaller standard errors. This reduction occurs because standard errors are affected by the correlation between variables as well as the sample size. It should be noted that adding more variables can lead to overfitting this is when the model becomes more complex and may start fitting noise rather than capturing true underlying relationships in the data. This can lead to a model that performs well on the training data but poorly on new, unseen data.

3. Ridge Regression - Ridge Regression achieves a delicate equilibrium between bias and variance, opting for a slight increase in bias to achieve a substantial reduction in variance. This method proves especially beneficial when handling datasets with pronounced multicollinearity or when the number of independent variables approaches or surpasses the number of dependent variables. Through the deliberate introduction of a modest amount of bias into the estimators, Ridge Regression effectively curtails the

variance of the estimators, thereby enhancing their stability even amidst multicollinearity.

According to Türsoy et al. (2008), the APT model does not specify the appropriate macroeconomic variables to be used. Hence, the elimination of variables is considered an appropriate approach, as there is no risk of excluding crucial variables that might lead to erroneous conclusions. Variables with VIF coefficients exceeding 10 will be systematically eliminated, beginning with those with the highest coefficients, until multicollinearity is successfully mitigated across all variables.

3.5. Primary Research Methodology

The primary research methodology for this study is time series regression model. Given that the objective of this research is to determine the impact of load shedding on SA REIT returns over time and the literature review analysis, an appropriate primary model for the research is the ARDL model (Sims, 1980) as the model is designed specifically for multivariate time series analysis and describes the relationships between variables based on their past values and the values of other variables. The independent variable will be the monthly load shedding megawatt shed and the dependent variable will be average monthly share price.

An appropriate primary model for the research is the ARDL model (Sims, 1980) as the model is designed specifically for multivariate time series analysis and describes the relationships between variables based on their past values and the values of other variables. The dependent variable for the model will be average monthly share price.

3.6. Preliminary Data Analysis

Prior to populating the variables in the ARDL model the data needs to be prepared to ensure that the Gauss Markov theorem applies and that Ordinary Least Squares estimators are Best Linear Unbiased Estimators.

3.7. Primary Model: ARDL Model Cointegration

3.7.1. Cointegration

Cointegration is a tool for modelling the long-run relationships in time series data between integrated variables and reparametrizing the relationship between the considered variables into an Error Correction Model (Pesaran and Shin 1999 and Pesaran et al. 2001). Cointegration is called the ARDL test.

The Wald test (F-statistics) is used to determine the bounds testing approach to determine the existence of cointegration among the independent variables, the order of integration of the variables and the lag structure results must be between the lower bound and upper bounds test of the critical values which is I(0) and I(1), respectively, the test can also have a combination of both bounds level (Pesaran and Pesaran, 1996a). If the test statistic exceeds the upper bound whereby variables, are I(2) order differencing then the null hypothesis is rejected and rendered invalid (Chigusiwa et al., 2011. The test is inconclusive if it falls between the bounds.

According to Nkoro and Uko (2016), the ARDL cointegration technique does not require preliminary test for unit root in variables that are integrated in the lower and upper bounds level order. However, conducting a unit root test becomes crucial in the presence of I(2) order differencing to prevent spurious results. Therefore, although not mandatory, it is still advisable to perform a unit root test.

The ARDL model is specified to include lagged levels of the variables and according to Sam, et al (2019) three tests need to hold in order to conclude that there is cointegration:

1. Overall F- statistical test on lagged level variables are found to be significant;
2. T-statistical test on the lagged level of the dependent variable is found to be significant; and
3. F-test on the lagged levels of the independent variables are found to be significant.

Should any of the variables not be statistically it may indicate degenerated of either dependent or independent variable cases which implies a case of no cointegration. The model is expressed as follows, using the Megawatts shed as independent variable, which is also known as the UPLC data:

$$\Delta RRTt = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta RRT_{t-i} + \sum_{j=1}^{q} \gamma_i \Delta LMW_{t-j} + \epsilon_t \quad (2)$$

Where:

- *$\Delta RRTt$: REIT returns at time t.*
- *ΔLMW_t: Megawatts shed at time t.Δ: First difference operator (to account for stationarity).*
- *α_0: Constant term.*
- *βi: Coefficients for lagged differences of REIT returns.*
- *γi: Coefficients for lagged differences of load shedding.*

The following is the null and the alternative hypothesis of cointegration model, where:

$$H_0 = \gamma_1 = \gamma_2 = 0 \;\; and \quad (3)$$

$$H_0 \neq \gamma_1 \neq \gamma_2 \neq 0 \quad (4)$$

Appropriate lags are assigned by Akaike Information Criteria (AIC). The AIC test serves to determine whether a long-run association exists among the study variables. If the bounds test suggests cointegration, the following step is to calculate the long run equilibrium and restricted Error Correction Model. This estimation allows for the measurement of both the short-run dynamic effects and the long-run equilibrium relationship between variables. As stated by Asafu-Adjaye (2000) and Masih and Masih (1996), short-run causality can be examined using the F-statistics from the Wald test to evaluate the significance of the coefficients, applying first differenced stationary variables.

The determination of a long-run relationship is based on the error correction term. If the error correction term is negative and statistically significant, it indicates the presence of a long-run relationship among the variables. Conversely, if the F-statistic falls below the critical value of the lower bounds, it suggests that there is no cointegration among the estimated variables. When the results confirm a long-run relationship, the ARDL model can be used to estimate the long-run elasticities.

As noted by Asafu-Adjaye (2000) and Masih and Masih (1996), the examination of short-run causality involves using the F-statistics from the Wald test to assess the significance of the relevant coefficients, utilizing first differenced stationary variables. The choice of the ARDL model for this study was guided by several methodological and empirical considerations. One of the key advantages of the ARDL approach is its flexibility in handling variables that are integrated of order zero, I(0), or order one, I(1), without requiring pre-testing for unit roots. This makes it particularly suitable for analysing both short- and long-term relationships in time series data. Moreover, the ARDL model performs well with small sample sizes, which is especially relevant given the limited availability of load shedding data for the study period.

Importantly, the ARDL framework facilitates the identification of how changes in load shedding patterns affect REIT performance in the short run while simultaneously capturing the dynamic adjustment toward long-run equilibrium. Even if REIT returns are stationary, the model can still test for long-run relationships by incorporating the lagged levels of the variables. This is achieved through the bounds testing procedure within the ARDL framework, which determines the existence of a long-run equilibrium relationship regardless of the integration order of the variables.

To ensure the validity of any identified long-run relationships, cointegration analysis is employed. This step confirms that the observed associations between REIT returns and load shedding are not spurious. A confirmed long-run relationship suggests that these variables move together over time, reinforcing the robustness of the model's findings.

3.7.2. ARDL Variables Robustness Test

A robustness test involves modifying certain analytical choices and examining how these changes affect the estimates of interest. It is used to assess the stability and reliability of the main results by testing them against plausible variations in model specifications (Neumayer and Plümper, 2017).

To address this objective a second ARDL model will be ran using electricity supply as the independent variable for robustness checks, this will be used because each variable captures different aspects of the electricity system. This approach is taken because each variable captures different aspects of the electricity system. The dual-model strategy helps account for potential distortions in regression estimates caused by extended periods without load shedding.

The megawatt-shed data may include periods with zero values, which could affect the regression outcomes.

According to Eskom (2024), load shedding was suspended for 240 consecutive days between 26 March 2024 and 19 November 2024, representing the longest stretch of uninterrupted electricity supply in South Africa over the past five years. Notably, prior to this period, the country experienced a record 332 days of load shedding in 2023, an increase from 205 days in 2022 (Eskom, 2024).

The model specification will remain the same as Model 2; however, instead of the variable ΔLMW_t variable ΔLES_t will be used, representing electricity supply.

The model is herein referred to as "New ARDL Model".

3.8. Secondary model: APT model

Ross (1976) introduced the APT as a broader and less constrictive framework compared to its precursor, the CAPM, for valuing risky assets. APT is a multi-factor asset pricing model that seeks to explain the relationship between the expected return of an asset and its risk by considering multiple systematic risk factors.

Unlike the CAPM, which relies on the single-factor model (systematic risk measured by beta), APT recognizes that asset returns may be influenced by several underlying factors beyond the market portfolio. These factors include macroeconomic variables Türsoy et al. (2008) recognise that the APT does not specify the appropriate macroeconomic variables to use; thus, any macroeconomic variables can be selected.

To further understand the effects of load shedding on REIT returns the APT model will be incorporated into the research and 10 macroeconomic variables as well Load shedding Megawatt shed (a microeconomic variable) will be included in the model.

Assumptions of the APT

Roll and Ross (1980) mention four fundamental APT model assumes which are:

- Perfectly competitive capital markets - APT assumes that markets are efficient and competitive, meaning that there are no transaction costs, no taxes, and no restrictions on trading. This assumption allows for the existence of arbitrage opportunities to be quickly exploited, leading to market prices that reflect all available information.

- Single-period model - APT typically operates within a single-period framework, where all relevant information is known at the outset. This simplifies the modelling process and facilitates the analysis of asset pricing under various scenarios.
- Linear relationship between risk and return - APT assumes that the relationship between the expected return of an asset and its exposure to systematic risk factors is linear. In other words, assets with higher exposure to systematic risk factors are expected to have higher expected returns, and vice versa.
- No arbitrage opportunities exist - APT assumes that there are no arbitrage opportunities in the market, meaning that investors cannot earn riskless profits by exploiting mispricing. This assumption is essential for the equilibrium pricing of assets based on their exposure to systematic risk factors.

These assumptions provide the foundation for the APT framework and guide its application in asset pricing and portfolio management.

3.8.1. APT Variables

In this research 10 macroeconomic variables are tested against 2 portfolios, in different numbers in each portfolio.

3.8.1.1. Independent Variables

The selected independent variables for this modelling are the following variables:

Variables full name	Description	Abbreviation
Megawatt shed	Used to measure load shedding, which refers to the amount of megawatts reduced from the national power system grid to ensure its stability. The megawatt reduction leads to various hours of power outages, known as load shedding stages. This is represented by UCLF.	MWs
Consumer Price Index	Is an indicator that measures the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. CPI is a measure of inflation rate. The impacts of CPI on REITs are addressed in the literature review section.	CPI

Money Supply	A key variable in South Africa's economy is the total amount of money in circulation, including cash, checking accounts, savings accounts, and other liquid assets. The Money Supply is monitored by the SARB. SARB identifies the money supply as comprising the Central Bank indicative rate, monetary policy rate, Treasury bill, Broad money supply, Currency in circulation, and other short-term interest rates of the financial market. These include the inter-bank call rate, savings rates, and other fixed deposit and lending rates (Olanrele et al., 2018). According to Olanrele et al. (2018), Broad money supply includes savings and time deposits (quasi-money), while net domestic credit represents the banking system's credit to the economy and consists of loans and advances provided by the Central Bank.	MS
Real GDP	A key variable is the economic activities and output in the real sector of an economy. Real GDP reflects the overall economic health and activity within a country, as it is the quantitative measure that captures the tangible, physical, or real aspects of economic production and performance. The impacts of Real GDP on REITs are addressed in the literature review section.	GDP
Imports	Imports refer to goods that arrive in South Africa via air, sea, road, rail, or post, including transmission commodities, for commercial purposes (SARS, 2023). Importing also includes the importation of services and is considered a reflection of the country's challenges in meeting its needs (Habanabakize, 2020). Rand appreciation leads to more imports than exports. When the Rand appreciates relative to other currencies, imports become cheaper for domestic consumers and businesses, while exports become more expensive for foreign buyers. Consequently, as the Rand appreciates, imported goods become relatively more affordable compared to domestically produced goods, leading to an increase in demand for imports.	IMP
Export	Exports refer to goods and services produced in South Africa and sold to buyers in foreign countries. Customs oversees the process of exporting goods, and records of exports are maintained by SARS. Exporting plays a crucial role in international trade, allowing countries to capitalize on their comparative advantages by selling goods that may not be in demand domestically but are sought after in foreign markets. It also provides opportunities for	EXP

	a country to expand its customer base, increase revenue, and access new growth opportunities.	
JSE Index	The JSE Index refers to a stock market index that tracks the performance of listed companies on the Johannesburg Stock Exchange, located in South Africa. The JSE Index provides investors with a benchmark to measure the overall performance of the South African stock market.	JSE
Dollar to Rand	Refers to the exchange rate between the United States dollar and the South African rand (ZAR). It indicates how many South African rand are needed to purchase one US dollar or vice versa. The ZAR_USD variable is included due to the dominance of the US dollar as the strongest currency globally. Economic globalization, which emerged significantly after the end of World War II, has fostered interdependence and interconnectedness among countries. Consequently, the US dollar has become the primary trading currency in the global economy and serves as the national currency of the United States (Schulmeister, 2000).	ZAR_USD
Gold Prices	The term refers to the market value of gold, a precious metal, per unit of weight, typically measured in troy ounces. Gold is widely traded as a commodity in financial markets, and its prices are influenced by various factors, making it a significant indicator for investors and economists.	GP
Brent Crude Oil Prices	The term refers to the market value of Brent crude oil, a major trading classification of sweet light crude oil that serves as a key benchmark for global oil prices. Brent crude is extracted from the North Sea and is widely used in pricing and trading crude oil worldwide.	BCO

Table 2: Independent macroeconomic variables and their description

Chen, Roll, and Ross (1986) demonstrate the significance of three macro variables in explaining anticipated stock returns. These variables are the term premium, default risk and monetary policy and inflation rate. Megawatt shed is also included as the explanatory variable. These variables have been included as part of the independent variables for this study. According to Ngo (2017) based on existing studies, the five key factors that affect the returns of REITs are size, book-to-market ratio, investor sentiment, inflation rate, and interest rate changes.

According to Rovolis and Feidakis (2012) in building a dynamic case model they presumed that the financial structure of a firm is influenced by a number of exogenous and endogenous variables. Exogenous variables are a makeup of time and macroeconomic, these factors characterize the influence of the external environment on the capital structure of the firm. While endogenous variables are a makeup of financial factors from the financial statements of the firm.

3.8.1.2.Dependent Variables

As of 2023, the JSE had 46 South African REIT companies listed, along with three non-South African REIT companies. For this study, 21 REITs were selected. The remaining REITs were excluded from the study due to the following reasons:

- 22 REIT companies were listed on the JSE after 2019, which falls outside the study period.
- 6 REIT companies are either under review or have been suspended from the JSE due to various

The REITs will be divided into two portfolios. The first portfolio consists of the top 10 listed REITs based on market capitalization, which collectively representing 90% of South Africa's REIT market capitalisation. Growthpoint Properties and Redefine Properties alone account for approximately half of the sector's market value (Hilton Tarrant, 2022). The second portfolio will comprise the remaining 11 REITs.

The portfolios' REIT Returns will be calculated to execute the APT model. The APT model, which is already addressed in the Literature Review, is based on the concept that the expected return of a portfolio can be determined using a linear relationship with multiple macroeconomic variables, thereby facilitating the estimation of the asset's price. Each factor influencing the asset's return is represented by a beta coefficient, denoting the degree of sensitivity of the asset's price to the respective factor. This conceptualization allows investors to leverage arbitrage opportunities, capitalizing on short-term discrepancies in asset prices to generate profits without exposure to risks (Ross, 1976).

The portfolio makeup contains the following REITs:

Portfolio A: Top 10 REITs	Portfolio B: Remining REITs
Growthpoint Properties, Redefine Properties, Vukile Property Fund Limited, Hyprop, Equities Properties, Attacq, Fairvest, Stor-Age Properties SA, SA Real Estate, Emira	Dipula, Accelarate, Acsion, Delta, Fortress REIT A, Octodec Investments, Resilient REIT, Safari Investments RSA, Spear REIT, Transcend Residential Property, Visual International Holding

Table 3: SA listed REITs that makeup Portfolio A and Portfolio

Model for the APT

The dataset will undergo tests to verify adherence to Ordinary Least Squares (OLS) assumptions outlined in section 3.5. Subsequently, the random returns on assets are modelled by the linear k-factor model, where the return of asset i is expressed as:

$$R_i = E_i + F_{i1}\beta_1 + F_{i2}\beta_2 + F_{i3}\beta_3 + \cdots + F_{ik}\beta_k + e_i \tag{5}$$

where:

- R_t *is the random rate of return on asset i;*
- E_i *is the expected return on asset i;*
- $F_{i1}, F_{i2}, F_{i3} \ldots F_{ik}$ *is the vector of common factors;*
- $\beta_1 + \beta_2 \ldots \beta_{ik}$ *denote the sensitivity of returns to the movement in common factors;*
- e_i *is the asset's idiosyncratic random shock with an expected mean of zero and constant variance.*

Formula (4) describes the return of asset i as a linear combination of its expected return, sensitivities to k common factors, and an idiosyncratic component e_i. This highlights the APT's approach of explaining asset returns based on the influence of multiple common factors plus asset-specific characteristics.

Both APT and CAPM incorporate the no-arbitrage principle, ensuring no risk-free profit opportunities due to mispricing in efficient markets. The APT formula embodies this multifactor approach, linking expected returns to the sensitivities and risk premiums of various macroeconomic factors. The equilibrium expected return of an asset is given by:

$$E_i = \lambda_0 + \lambda_1 F_{i1} + \lambda_2 F_{i2} + \cdots + \lambda_k F_{ik} \quad (6)$$

Where:

- *E_i is the expected return on asset i;*
- *$\lambda_1, \lambda_2, \lambda_3 \ldots \lambda_k$ Factor weights representing the risk premiums associated with each common factor*

The APT framework captures this multifactorial approach, illustrating how expected returns are influenced by the systematic risks associated with various macroeconomic factors. Summary: Formula (5) expresses the expected return of asset i in terms of a linear combination of factor sensitivities F_{ik} and corresponding factor weights λ_k. This equation illustrates how the expected return is determined by the asset's exposure to the identified common factors and the associated risk premiums.

These two formulations constitute the core of the APT model, assuming that the expected return on an asset is influenced by multiple macroeconomic factors, with beta capturing the asset's sensitivity to each factor. The data analysis proceeds in a time series regression where the beta value of each macroeconomic factor is regressed against the average return of each stock. The primary focus lies on the MW variable, which serves as a pivotal element in this study.

3.8.2. Robustness Test for APT model

Three independent variables will be included in the robustness test model that will be included which were not included in the first model outcome, there variables are collectively herein referred to as the "New Variables":

Covid-19	The term refers to a contagious respiratory illness caused by the novel coronavirus SARS-CoV-2. The World Health Organization declared Covid-19 a global pandemic on March 11, 2020 (World Health Organization, 2020). While the virus is still present and managed like other infectious diseases, the World Health Organization declared the end of COVID-19 as a global public health emergency on May 5, 2023 (World Health Organization, 2023).	COV

	SA recorded its first confirmed case of COVID-19 on 5 March 2020. The patient was a 38-year-old man who had returned from a trip to Italy. (Mkhize, 2020). Subsequently, on 23 March 2020, President Cyril Ramaphosa announced a 21-day national lockdown to commence at midnight on 26 March 2020, in an effort to curb the spread of the virus. (Ramaphosa, 2020). The country's COVID-19 national state of disaster officially ended on 4 April 2022 (Ramaphosa, 2022). This marked the lifting of most emergency regulations that had been in place. For this study, the COVID-19 pandemic period will be recorded from the month of March 2020, when the South African president announced the national lockdown, until the month of April 2022, when the national state of disaster ended.	
Industrial Production Index	The variable tracks the changes the volume of output produced by industries such as manufacturing, mining, and utilities over time. The IPI helps track the strength and growth of the industrial economy	IPI
Electricity Supply	refers to the total amount of electrical energy generated and made available to meet the demand of consumers. Electricity supply serves as an indicator of the stability and adequacy of the national power system, reflecting both generation capacity and operational reliability.	ES

For the robustness test concerning the APT model, 3 various models will be ran:

1. APT model with MWs variable plus New Variables;
2. APT model with ES variable plus the existing variables;
3. APT model with ES variable plus New Variables.

3.9 Ethical considerations

All data for this research will be sourced from secondary sources, including REIT websites and integrated annual reports. As a result, there is no need to consider ethical implications related to data collection in this research.

4. Model Estimation and Results

4.1. Introduction

In this chapter, the research methodology is applied to analyse the research data. The results of the data analysis are presented in the form of graphs, charts, and tables. This section focuses on presenting the descriptive analysis and the regression results.

4.1.1. Collection and Adjustment of Data

4.1.1.1. Data Collection

It was originally intended for the data analysis period to span from 2014 to 2022; however, this timeframe was revised and now covers the period from April 2019 to December 2023. This adjustment was necessary due to the limitation in the availability of Eskom's load shedding data, which has been available only for 5 years, starting from 2019.

4.1.1.2. Variable Adjustment

Variable	Adjustments
Megawatt Shed	Load shedding data was extracted from the Eskom website's database and the data is recorded on an hourly basis, the UCLF data has been converted from a high hourly frequency to a low monthly frequency using the technique described in section 3.4.2.
Inflation Rate	The inflation rate was calculated from the CPI, using the following formula: $$INF = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100 \quad (7)$$ *INF = Inflation rate,* CPI_t *= Current CPI,* CPI_{t-1} *= Previous CPI*
Real GDP growth rate	The real GDP growth rate was calculated using the following formula: $$GDP = \frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 \quad (8)$$ *GDP = real GDP growth rate,* GDP_t *= Current real GDP,* GDP_{t-1} *= Previous real GDP*
Brent Crude Oil & Gold	The prices of Brent Crude Oil and Gold are denominated in US Dollars and were converted to Rands by multiplying each result by 18.5, which is the average annual exchange rate of the Dollar to the Rand in 2023.
Covid-19	Given the qualitative nature of the COVID-19 pandemic and the difficulty in directly quantifying its impact, a dummy variable will be employed in the analysis. This variable will take the value of 1 to indicate periods during

	the COVID-19 pandemic, and 0 to represent periods either before or after the pandemic.

Table 4: Variable Adjustment Technique

4.1.1.3. Logarithmic Transformation

All variables outlined in section 3.3 underwent logarithmic transformation, except for COV, INF, GDP, Portfolio A and Portfolio B. This exception was made due to the presence of negative values within these variables. Not applying the logarithmic transformation to these variables is not a concern, as the rate of change of the variables was used instead.

The purpose and benefits of taking the natural logarithm of variables are to:

1. Stabilise variance across different levels of the independent variable, making the model more robust and reliable.
2. Logging data can transform non-linear relationships into linear ones, allowing for simpler and more interpretable regression models. This transformation can improve the accuracy of estimation and enhance the validity of statistical inferences drawn from the data.
3. Logging data can also help to reduce the impact of outliers, making the analysis more resilient to extreme observations.

4.2. Data Analysis

4.2.1. Descriptive Data Analysis

Descriptive analysis is the first step first step in data analysis and the purpose is to comprehend the structure and characteristics of a dataset before progressing to more advanced analyses or hypothesis testing. In this section, the following techniques will be employed: measures of central tendency and measures of dispersion. These methods will be utilized to summarize and describe the primary features of the dataset.

4.2.1.1. Descriptive Statistic

Table 5 presents the results of the descriptive analysis from log-transformed sample data variables which shows the characteristics of the data set. The sample includes 57 observations and the summary statistic are represented below.

Descriptive Statistics													
Variables	LRRT	Portfolio A	Portfolio B	LBCO_ZAR	LINF	LEXP	LGD_ZAR	LGDP	LIMP	LJSE	LMS	LMWS	LZAR_USD
Mean	8,2344	0,1121	-1,0096	4,2375	-0,3073	0,4663	7,4322	0,2502	-2,2069	11,0758	0,8763	8,4538	2,7860
Std. Dev	0,1673	0,0225	0,0826	0,3040	0,2759	0,1979	0,1459	1,3277	0,9708	0,1457	0,6124	0,2303	0,0992
Skewness	-0,4935	0,3157	2,6176	-0,9327	0,3261	-0,4659	-0,7571	-0,5090	-6,6277	-0,4037	3,8692	-0,5437	0,2468
Kurtosis	1,9422	2,1654	2,4493	4,0685	3,8259	1,7577	2,1992	2,9480	47,8704	2,1210	50,1677	2,8940	1,7788
Jarque-Bera	0,0873	0,0125	0,0000	0,0067	0,2747	0,0600	0,0326	0,2975	0,0000	0,1898	0,0000	0,2484	0,1321

Table 5: Descriptive Statistic Table
Std. Dev = Standard Deviation, Jacque Bera = Probability value of Jarque-Bera.

The results indicate LJSE records the highest mean value while LIMP records the lowest mean value. The standard deviation shows minimal deviation of series from their means across all variables. Skewness measures the degree of asymmetry of the series and result indicate that LRRT, LBCO_ZAR, LEXP, LGD_ZAR, LIMP, GDP, LJSE and LMWs are negatively skewed, implying long left tails with values lower than their observed means. Conversely, Portfolio A, Portfolio B, INF and LMS exhibit positive skewness, indicating long right tails with values higher than their observed means.

Kurtosis measures the peakiness or flatness of the distribution of the series and results indicate that all series are leptokurtic i.e., they peaked curves and thus have higher kurtosis values.

The Jarque-Bera test serves to summarize the results of skewness and kurtosis, providing insights into the normality of the dataset. The results indicate that all series conform to a normal distribution, except for LBCO_ZAR, LGD_ZAR, LIMP, and LMS, which exhibit very low p-values, thus rejecting the null hypothesis of a normal distribution. Further test of normal distribution is discussed in 4.3.4 whereby the normality test was conducted.

New variable results

Descriptive Statistics			
Variables	LES	LIPI	COV
Mean	10,2350	4,5251	0,4561
Std, Dev	0,1006	0,1055	0,5025
Skewness	-0,1643	-4,6340	0,1761
Kurtosis	1,8786	28,0008	1,0310
Jarque-Bera	0,1975	0,0000	0,0086

Table 6: descriptive statistics for New Variables

The results in table 6 indicate LES records the highest mean value while COV records the lowest mean value. The standard deviation shows minimal deviation of series from their means across all variables.

Skewness results indicate that LES and LIPI are negatively skewed, implying long left tails with values lower than their observed means. Conversely, COV exhibit positive skewness, indicating long right tails with values higher than their observed means.

The Jarque-Bera test results indicate that all series conform to a normal distribution, except for LES, which exhibit very low p-values, thus rejecting the null hypothesis of a normal distribution.

4.3. Diagnostic Test

4.3.1. ADF - Stationarity Test

The time series properties of the variables used in the analysis was investigated using ADF test. The test was run with specification of trend and intercept in the model. The ADF statistics for the test are presented in table 6 and 7.

4.3.1.1. Macroeconomic Variables – Stationarity Test

A trend and an intercept were employed for the testing for stationarity in levels and at 1st differencing. Table 6 below shows that all the variables are non-stationary in levels (null hypothesis is rejected) at the 5% level, except for the INF, LIMP, LMS and LMWs which were stationary at the levels. However, all the other variables became stationary after first differencing.

No.	Variable	Model	Lag	ADF test statistic	1% Level	5% Level	10% Level	Probability	Decision
1	LRRT	Trend & Intercept	0	-2,1227	-4,1305	-3,4921	-3,1748	0,5221	Not Stationary
	D(LRRT)	Trend & Intercept	0	-8,3253	-4,1338	-3,4937	-3,1757	0,0000	Stationary
2	LBCO_ZAR	Trend & Intercept	0	-2,3463	-4,1305	-3,4921	-3,1748	0,4029	Not Stationary
	D(LBCO_ZAR)	Trend & Intercept	0	-7,2930	-4,1338	-3,4937	-3,1757	0,0000	Stationary
3	INF	Trend & Intercept	1	-6,9499	-4,1373	-3,4953	-3,1766	0,0000	Stationary
	D(INF)	Trend & Intercept	5	-6,5613	-4,1567	-3,5043	-3,1818	0,0000	Stationary
4	GDP	Trend & Intercept	0	-2,7740	-4,1338	-3,4937	-3,1757	0,2128	Not Stationary
	D(GDP)	Trend & Intercept	0	-5,3928	-4,1338	-3,4937	-3,1757	0,0002	Stationary
5	LEXP	Trend & Intercept	0	-1,6213	-4,1305	-3,4921	-3,1748	0,7719	Not Stationary
	D(LEXP)	Trend & Intercept	0	-7,2133	-4,1338	-3,4937	-3,1757	0,0000	Stationary
6	LGD_ZAR	Trend & Intercept	0	-1,8856	-4,1305	-3,4921	-3,1748	0,6487	Not Stationary
	D(LGD_ZAR)	Trend & Intercept	0	-7,2905	-4,1338	-3,4937	-3,1757	0,0000	Stationary
7	LIMP	Trend & Intercept	0	-7,2072	-4,1305	-3,4921	-3,1748	0,0000	Stationary
	D(LIMP)	Trend & Intercept	0	-8,7668	-4,1373	-3,4953	-3,1766	0,0000	Stationary
8	LJSE	Trend & Intercept	0	-2,8180	-4,1338	-3,4937	-3,1757	0,1972	Not Stationary
	D(LJSE)	Trend & Intercept	0	-7,6690	-4,1338	-3,4937	-3,1757	0,0000	Stationary
9	LMS	Trend & Intercept	0	-7,3066	-4,1305	-3,4921	-3,1748	0,0000	Stationary
	D(LMS)	Trend & Intercept	1	-8,6684	-4,1373	-3,3495	-3,1766	0,0000	Stationary
10	LMWS	Trend & Intercept	1	-4,5460	-4,1338	-3,4937	-3,1757	0,0031	Stationary
	D(LMWS)	Trend & Intercept	0	-6,4866	-4,1756	-3,5131	-3,1869	0,0000	Stationary
11	LZAR_USD	Trend & Intercept	0	-2,0624	-4,1305	-3,4921	-3,1748	0,5549	Not Stationary
	D(LZAR_USD)	Trend & Intercept	0	-6,6564	-4,1338	-3,4937	-3,1757	0,0000	Stationary

Table 7: ADF Unit test results.

4.3.1.2. JSE listed SA REIT Variables – Stationarity Test

Table 7 below presents the results for Portfolio A and Portfolio B results and indicates that Portfolio A is non-stationary at levels however, stationary after first differencing. While Portfolio B is stationary at level.

No.	Variable	Model	Lag	ADF test Statistic	1% Level	5% Level	10% Level	Probability	Decision
1	Portfolio_A	Trend & Intercept	4	-2,5191	-4,1446	-3,9487	-3,1786	0,3181	Not Stationary
	D(Portfolio_A)	Trend & Intercept	3	-7,0569	-4,1446	-3,9487	-3,1786	0,0000	Stationary
2	Portfolio_B	Trend & Intercept	0	-7,8608	-4,1305	-3,4921	-3,1748	0,0000	Stationary

Table 8: ADF Unit test results for JSE listed SA REITS.

4.3.1.3. New Variables – Stationarity Test

Table 8 below presents the results for New Variables and indicates that LES and COV are not stationary at levels however, stationary after first differencing. While LIPI is stationary at level.

No.	Variable	Model	Lag	ADF test statistic	1% Level	5% Level	10% Level	Probability	Decision
1	LES	Trend & Intercept	2	-2,7631	-3,5574	-2,9166	-2,5961	0,0704	Not Stationary
	D(LES)	Trend & Intercept	4	-4,6863	-3,5654	-2,9200	-2,5979	0,0004	Stationary
2	COV	Trend & Intercept	0	-1,7475	-4,1305	-3,4921	-3,1748	0,7166	Not Stationary
	D(LCOV)	Trend & Intercept	0	-7,3937	-4,1338	-3,4937	-3,1757	0,0000	Stationary
3	LIPI	Trend & Intercept	0	-4,4714	-4,1305	-3,4921	-3,1748	0,0038	Stationary

Figure 8: ADF Unit test results for New Variables.

Unit roots refer to characteristics of time series data that indicate non-stationarity are patterns where the data does not settle around a constant mean over time but instead tends to drift or wander. Unit roots are non-stationary autoregressive or autoregressive moving average time series processes, which may include an intercept and a trend. In this section, the ADF test was used determine whether the variables possess a unit root or not.

Having unit root can lead to spurious regression results, resulting in unreliable forecasting and misleading interpretations of the model. The unit root tests were conducted by applying the ADF test to assess the stationarity of all the log-transformed variables.

4.3.2. KPPS Test - Stationarity Test

The KPSS test is a non-parametric alternative to the ADF test. While both ADF and KPSS tests are based on regressing differenced time series data on lagged differences of itself to detect the presence of a unit root, the KPSS test differs from the ADF test in its treatment of the error structure. Specifically, the KPPS test does not impose strict assumptions about the autocorrelation structure of the errors, making it more robust to heteroscedasticity and autocorrelation in the residuals. In contrast, the ADF test relies on specific distributions, such as the t-distribution, to obtain critical values and may assume different trend specifications in the data, allowing for greater flexibility in modelling trends.

The results from the ADF test differ from KPSS because KPSS does not provide a p-value; instead, it presents different critical values. In this scenario, the test statistic value is compared with the critical value at the desired significance level. If the test statistic exceeds the critical value, the null hypothesis is rejected; conversely, if the test statistic is lower than the critical value, the null hypothesis cannot be rejected. The results in table 8 below were the same in terms of the level at which stationarity was achieved however the bandwidth of the KPSS test was at a higher level for all the variables except for logged GD_ZAR, MS, LZAR_USD and IMP at level.

No.	Variable	Model	Bandwidth	KPSS test statistic	1% Level	5% Level	10% Level	Decision
1	LRRT	Trend & Intercept	1	-2,0742	-4,1305	-3,4921	-3,1748	Not Stationary
	D(LRRT)	Trend & Intercept	4	-8,5619	-4,1338	-3,4937	-3,1757	Stationary
2	LBCO_ZAR	Trend & Intercept	3	-2,3275	-4,1305	-3,4921	-3,1748	Not Stationary
	D(LBCO_ZAR)	Trend & Intercept	6	-7,3335	-4,1338	-3,4937	-3,1757	Stationary
3	INF	Trend & Intercept	26	-5,1363	-4,1338	-3,4937	-3,1757	Stationary
	D(INF)	Trend & Intercept	18	-14,7355	-4,1373	-3,4953	-3,1766	Stationary
4	GDP	Trend & Intercept	1	-2,2401	-4,1305	-3,4921	-3,1757	Not Stationary
	D(GDP)	Trend & Intercept	7	-5,1318	-4,1338	-3,4937	-3,1757	Stationary
5	LEXP	Trend & Intercept	1	-1,6855	-4,1305	-3,4921	-3,1748	Not Stationary
	D(LEXP)	Trend & Intercept	4	-7,2105	-4,1338	-3,4937	-3,1757	Stationary
6	LGD_ZAR	Trend & Intercept	2	-1,9637	-4,1305	-3,4921	-3,1748	Not Stationary
	D(LGD_ZAR)	Trend & Intercept	0	-7,2905	-4,1338	-3,4937	-3,1757	Stationary
7	LIMP	Trend & Intercept	0	-7,2067	-4,1305	-3,4921	-3,1748	Stationary
	D(LIMP)	Trend & Intercept	54	-52,8945	-4,1373	-3,4937	-3,1757	Stationary
8	LJSE	Trend & Intercept	1	-2,8700	-4,1305	-3,4921	-3,1748	Not Stationary
	D(LJSE)	Trend & Intercept	3	-7,6810	-4,1338	-3,4937	-3,1757	Stationary
9	LMS	Trend & Intercept	0	-7,3066	-4,1305	-3,4921	-3,1748	Stationary
	D(LMS)	Trend & Intercept	54	-54,4248	-4,1338	-3,4936	-3,1766	Stationary
10	LMWS	Trend & Intercept	4	-3,9484	-4,1305	-3,4921	-3,1748	Stationary
	D(LMWS)	Trend & Intercept	17	-8,8608	-4,1338	-3,4937	-3,1757	Stationary
11	LZAR_USD	Trend & Intercept	0	-2,0624	-4,1305	-3,4921	-3,1748	Not Stationary
	D(LZAR_USD)	Trend & Intercept	4	-6,6117	-4,1338	-3,4937	-3,1757	Stationary

Table 9: KPPS Test Result

Portfolio A and Portfolio B were both non-stationary at level, however, are stationary after first difference. The bandwidth for Portfolio B is 55. The bandwidth parameter in KPSS test kernel density estimation determines the width of the kernel function, which in turn affects the smoothness of the estimated density function. A high bandwidth results in a smoother estimate of the density function. This means that the resulting density curve will be less sensitive to local fluctuations or noise in the data, reducing the test's sensitivity to detecting deviations from stationarity.

No.	Variable	Model	Brandwidth	KPSS test Statistic	1% Level	5% Level	10% Level	Decision
1	Portfolio_A	Trend & Intercept	3	0,0659	0,2160	0,1460	0,1190	Not Stationary
	D(Portfolio_A)	Trend & Intercept	9	0,0000	0,2160	0,1460	0,1190	Stationary
2	Portfolio_B	Trend & Intercept	1	0,0568	0,2160	0,1460	0,1190	Not Stationary
	D(Portfolio_B)	Trend & Intercept	55	0,5000	0,2160	0,1460	0,1190	Stationary

Table 10: KPSS test results for JSE listed SA REITS.

LES and COV were both non-stationary at level, however, are stationary after first difference. The bandwidth for LIPI is 45.

No.	Variable	Model	Band width	KPSS test statistic	1% Level	5% Level	10% Level	Decision
1	LES	Trend & Intercept	4	0,1164	0,2160	0,1460	0,1190	Not Stationary
	D(LES)	Trend & Intercept	2	0,0409	0,2160	0,1460	0,1190	Stationary
2	COV	Trend & Intercept	6	0,1968	0,2160	0,1460	0,1190	Not Stationary
	D(LCOV)	Trend & Intercept	2	0,0751	0,2160	0,1460	0,1190	Stationary
3	LIPI	Trend & Intercept	3	0,0726	0,2160	0,1460	0,1190	Stationary
	D(LIPI)	Trend & Intercept	45	0,4090	0,2160	0,1460	0,1190	Stationary

Table 11:KPSS test results for New Variables

4.3.3. Autocorrelation

Table 12 presents the tests conducted to assess autocorrelation using the logged variables of LRRT, Portfolio A and Portfolio B as the dependent variables and logged independent variables attributed to both the ARDL model and APT model. The first test conducted was the Durbin-Watson test and the second test, the Serial Correlation LM test.

Independent Variable	Dependent Variable	Correcting Autocorrelation	Durbin-Watson Stat	Prob. F	Prob. Chi-Square
LRRt	LMWs	No lagged variable	0,1679	0	0
		Lagged variable	2,1589	0,2289	0,2074
Portfolio A	Macroeconomic variables	No lagged variable	2,2021	0,5128	0,4409
Porfolio B	Macroeconomic variables	No lagged variable	1,9149	0,9682	0,9606

Table 12: Autocorrelation Test for ARDL, Portfolio A and Portfolio B.
Prob. F = F-statistic Probability, Prob. Chi-Square = R-Square Probability.

Results for New Regression

Independent variable	Dendent Variables	Correcting Autocorrelation	Durbin-Watson Stat	Prob. F	Prob, Chi-Square
LRRT	LES	No lagged variable	0,3744	0,0000	0,0000
		lagged variable	2,1286	0,2321	0,2104
Portfolio A	Macroeconomic Variables	No lagged variable	2,0682	0,9377	0,9113
Portfolio B	Macroeconomic Variables	No lagged variable	2,0120	0,9649	0,9478

Table 13: Autocorrelation Test for New Regression

The presence of autocorrelation violates the assumption of independence among observations, which is fundamental in many statistical analyses. This violation can lead to biased parameter estimates and unreliable statistical inferences. Autocorrelation can indicate the presence of trends or patterns, influencing trading strategies and risk management techniques.

Introducing lagged variables improves autocorrelation by incorporating past values of the dependent variable into the regression model. By introducing lagged variables, the model accounts for the relationship between the current observation and its previous values, thereby capturing any temporal dependencies present in the data. This inclusion allows the model to better capture the underlying patterns and dynamics, reducing the presence of autocorrelation in the residuals. Essentially, lagged variables enable the model to better account for the autocorrelated structure of the data, resulting in more accurate parameter estimates and reliable statistical inferences.

4.3.3.1. Results for ARDL model

The first test conducted was the Durbin-Watson test and the model yielded a result of 0.1679, falling below the range of 1.5-2.5. The result indicates positive evidence of autocorrelation in the regression outcomes. The LM test was conducted as a follow-up to confirm the findings from the Durbin-Watson test. The LM test yielded F-statistics and R-Square probabilities of 0.00 for both, which is below 0.05, suggesting evidence of serial correlation in the results.

Autocorrelation was addressed by introducing a one-period lagged variable of LRRT, the dependent variable, thereafter the tests were reconducted. The Durbin-Watson test resulted in an improved value of 2.1589, falling within the acceptable range of 1.50 to 2.50 and indicating that autocorrelation had been corrected. The Serial Correlation LM test yielded F-statistics and

R-Square probabilities of 0.2289 and 0.2074, respectively. Both sets of values exceeded 0.05, suggesting no evidence of serial correlation in the results.

4.3.3.2. Results for Portfolio A and B model

Results for Portfolio A and B models include initial tests for autocorrelation. The Durbin-Watson test produced values of 2.2021 for Portfolio A and 1.9149 for Portfolio B, both falling within the acceptable range of 1.5-2.5, indicating no significant autocorrelation in the regression results. To further validate these findings, an LM test was conducted. The LM test generated F-statistics of 0.5128 and 0.9682 for Portfolio A and B, respectively, along with R-Square probabilities of 0.4409 and 0.9606. These results, with values exceeding 0.05, confirm the absence of serial correlation in the models.

4.3.3.3. Results for New Regression

The results for the ARDL model based on the LES variable, the Durbin-Watson test yielded a result of 0.3744, falling below the acceptable range. The result indicates positive evidence of autocorrelation in the regression outcomes. The second results demonstrate the outcome after including one lagged dependent variable which yielded the Durbin-Watson results of 2,1286 indicating no significant autocorrelation in the regression results. Furthermore the LM test was conducted and the F-statistics results along with R-Square probabilities exceed 0.05, confirming the absence of serial correlation in the models.

Results for Portfolio A and B models include initial tests for autocorrelation. The Durbin-Watson test produced values of 2,0682 for Portfolio A and 2,0120 for Portfolio B, both falling within the acceptable, indicating no significant autocorrelation in the regression results. The LM test results for F-statistics as well as the R-Square probabilities exceed 0.05, confirming the absence of serial correlation in the models.

4.3.4. Normality Test

The normality of error terms was tested using the correlogram diagram, and the results for both ARDL and APT models indicated no evidence of non-normality. The probability results of the Jarque-Bera test exceeded the 5% level of significance. The results were as follows:

	Jacque Bera	P-value
ARDL	4.0675	0.1308
Portfolio A	0.5425	0.7624
Portfolio B	2.1976	0.3333

Table 14: Normality Test Results

The normality of error terms was tested using the correlogram diagram on the New Models demonstrate no evidence of non-normality on all the New Models. The probability results of the Jarque-Bera test exceeded the 5% level of significance. The results were as follows:

	Jacque Bera	P-value
ARDL	3,3956	0,1831
Portfolio A	0,6876	0,7091
Portfolio B	0,2671	0,8750

Table 15:Normality Test Results for New Models

Addressing non-normality in regression analysis ensures the reliability of results, as its presence can undermine the validity of the statistical tests and confidence intervals derived from the model.

4.3.5. Heteroskedasticity

Heteroskedasticity for the ARDL model is addressed in 4.4.1.1. For Portfolio A and B, the Breusch-Pagan Godfrey test was conducted and yielded the following results:

	Prob. F	**Prob. Chi- Square**
Portfolio A	0,0705	0,0793
Portfolio B	0,4558	0,4260

Table 16: Heteroskedasticity Results using the Breusch-Pagan Godfrey Test

Both the Portfolios are homoscedastic.

The second test conducted was White test and the following results were yielded:

	Prob. F	**Prob. Chi- Square**
Portfolio A	0,0667	0,0983
Portfolio B	0,0786	0,2214

Table 17: Heteroskedasticity Results using the White Test

Both portfolios are homoscedastic.

Heteroskedasticity for New APT model using the Breusch-Pagan Godfrey test was conducted and the results are demonstrated below as follows:

	Prob. F	**Prob. Chi-Square**
Portfolio A	0,3253	0,3075
Portfolio B	0,9111	0,8689

Table 18: Heteroskedasticity Results using the Breusch-Pagan Godfrey Test on the New APT model

Both the Portfolios are homoscedastic.

4.4. ARDL Model

The first objective of this study is to examine the impact of load shedding on SA REIT returns. Through the ARDL method to establish a short and long-term relationship between load shedding and SA REIT returns. The ARDL method is the preferred method for the bivariant variable analysis. In estimating the ARDL model for this study, the following procedure is followed. The ARDL procedure requires all variables to be stationary at either I(0) or I(1), with none at I(2), which we have already tested for unit roots in section 4.2.2. LMWs was stationary at level, and LRRT was stationary after first differencing. The stationarity test was conducted in order to avoid having a spurious regression result. The ARDL expression of the cointegration test equation is represented below.

4.4.1. Regression Analysis

4.4.1.1. Long Run and Bound Cointegration Test

As a result of having the LMW's and LRRT stationary at different level, it means that there is a mixed order of integration, a bounce test is required to test if the variables have a long run relationship among themselves. Using the Akaike Information Criterion (AIC), and trend the results were as follows:

Variable	Beta Coefficient	t-statistic	p-value
LRRT (-1)	0.9390	20.4076	0.0000
LMWs	0.0114	0.4412	0.6609
C	0.4146	1.0776	0.2861

Table 19: AIC Test Results

Further to the AIC test, White's heteroscedasticity-consistent covariance matrix estimator, was selected to address the issue of heteroscedasticity in regression analysis. The presence of heteroscedasticity violates one of the assumptions of classical linear regression, which assumes homoscedasticity (constant variance of errors). The White coefficient covariance matrix estimator adjusts the standard errors of the regression coefficients to correct for heteroscedasticity. By doing so, it produces more reliable estimates of the coefficients' standard errors, t-statistics, and confidence intervals.

The inclusion of the AIC test in the model resulted in appropriate lags being assigned to the regression; in this instance, the LRRT(-1) variable was incorporated. The AIC helps determine the optimal lag length for the variables in the model. Including lag variables allows the model to capture the temporal dependencies in the data. However, including too many lag variables can lead to overfitting, where the model fits the noise in the data rather than the underlying patterns.

The trend variable is insignificant as it exceeds 0.05. The bounce test was conducted using the long run form in EViews and the following results were produced:

F-Bound Test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic k	1.0536	10%	3.0200	3.5100
		5%	3.62	4.1600
		2.5%	4.18	4.7900
		1%	4.94	5.5800

Table 20: Bounds Test Results

From the results in Table 20, it is observed that the F-statistic is lower than the critical value for I(0), the lower bound test. Therefore, the null hypothesis of no level relationship cannot be rejected. Consequently, the series are not cointegrated, indicating the absence of a long-run relationship. Thus, it seems that Megawatt Shed does not significantly impact the prices of South African REITs over time. Although the coefficient relationship for Megawatt shed was found to be positive, it was statistically insignificant. This could be attributed to the limitations posed by the restricted research period and the exclusion of other variables that may influence REIT prices. The next step involves regressing the short-run model.

4.4.1.2. Short Run Relationship

Based on the conclusion reached in section 4.4.1.1, where no long-run relationship was found, a short-run test is conducted by differencing all variables by one position. The absence of a long-run relationship between variables suggests that they may exhibit short-run dynamics or fluctuations that are not captured by a simple linear relationship. By differencing the variables, the analysis focuses on the changes or deviations from the mean rather than the absolute levels of the variables, revealing the short-term relationships between the variables. In essence, differencing helps to isolate and analyse the short-term dynamics. The results of the model are as follows:

Variable	Beta Coefficient	t-statistic	p-value
D(LRRT (-1))	-0,1397	-1,0085	0,3181
D(LRRT (-2))	-0,2092	-1,5133	0,1365
D(LMWs)	0,0038	0,1362	0,8922
C	0,0115	0,1362	0,1332
R-squared	0,0556		
Adj. R-squared	-0,0192		
F-statistic	0,7499		
DW stat	1,9752		

Table 21: Short Run Results

All the variables are insignificant, with p-values above the 5% significance. The R-squared is very low at 0.0556, which tells us that the model is a poor fit and a weak relationship between the independent variables and the dependent variable. Durbin-Watson yielded a result of 1.975, is within the range of 1.50 to 2.50. Thus, serial correlation has been adequately corrected. In the short run, there appears to be a positive, but insignificant, relationship between MWs and RRT. The insignificant coefficient results of LMWs indicates that changes in the LRRT variable are not explained by the LMWs variable, consistent with the long run results. However, the R-squared value of 5.56% indicating that only a small proportion of variation in LMW is explained by LRRT. The low explanatory power of the model makes it difficult to draw firm conclusions regarding the impact of load shedding on SA REIT prices. In Section 4.5, an alternative estimation technique is used to test the relationship.

4.4.2. Regression Analysis – New ARDL Model

4.4.2.1. Long Run and Bound Cointegration Test

Bounce test was conducted to test if the variables have a long run relationship among themselves. The model selection was based on the AIC and a trend component was included and presented the following results:

Variable	Beta Coefficient	t-statistic	p-value
LRRT(-1)	0,9211	17,1784	0,0000
LES	0,0675	0,1764	0,4484
C	-0,0331	-0,0441	0,9649

Table 22: AIC Test Results for New ARDL Model

The lag of the dependent variable is significant this indicates that the previous period's value of the dependent variable has a strong and statistically significant effect on its current value. The LES variable and constant are insignificant, with p-values above the 5% significance. This suggests that there is no evidence of a long-run relationship among the variables.

Despite the lack of long-run significance, the model's R-squared value is relatively high at 0.8958, indicating that approximately 89.58% of the variation in the dependent variable is explained by the independent variables. Durbin-Watson yielded a result of 2.1286, which falls within the range of 1.50 to 2.50. This implies that serial correlation is not present in the model, and the residuals are independently distributed.

The model is statistically well-behaved in terms of fit and residual diagnostics. However, there is no evidence of a long-run equilibrium relationship between electricity supply and LRRT, as indicated by the insignificance of the LES variable in the long-run regression.

The trend variable is insignificant as it exceeds 0.05. The bounce test was conducted using the long run form in EViews and the following results were produced:

F-Bound Test				
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic k	1,1903	10%	3,02	3,51
		5%	3,62	4,16
		2,50%	4,18	4,79
		1%	4,94	5,58

Table 23: Bounds Test Results for New ARDL Model

From the results in Table 16, the F-statistic is lower than the critical value for I(0), the lower bound. Therefore, the null hypothesis of no level relationship cannot be rejected. This indicates that the variables are not cointegrated and that there is no evidence of a long-run relationship among them. Consequently, electricity supply does not appear to have a significant long-term impact on the prices of South African REITs. Although the coefficient for electricity supply was positive and the model showed a strong overall fit, the variable itself was statistically insignificant. This could be attributed to the limitations posed by the restricted research period and the exclusion of other variables that may influence REIT prices. The next step involves regressing the short-run model.

4.4.2.2. Short Run Relationship – New ARDL model

The short run model for New ARDL model results of the model are as follows:

Variable	Beta Coefficient	t-statistic	p-value
D(LRRT(-1))	-0,1410	-1,0206	0,3123
D(LRRT(-2))	-0,2102	-1,5146	0,1362
D(LES)	0,0104	0,0967	0,9234
C	0,0117	1,5476	0,1280
R-squared	0,0554		
Adj, R-squared	-0,0013		
f-statistc	0,9773		
DW stat	1,9793		

Table 24: Short Run Results for New ARDL Model

All the variables are insignificant, with p-values above the 5% significance. The R-squared is very low at 0.0554, which tells us that the model is a poor fit and a weak relationship between the independent variables and the dependent variable. Durbin-Watson yielded a result of 1.979, is within the range of 1.50 to 2.50. Thus, serial correlation has been adequately corrected. In the short run, there appears to be a positive, but insignificant, relationship between LES and

RRT. The insignificant coefficient results of LES indicates that changes in the LRRT variable are not explained by the LES variable, consistent with the long run results. However, the R-squared value of 5.54% indicating that only a small proportion of variation in LMW is explained by LRRT. The low explanatory power of the model makes it difficult to draw firm conclusions regarding the impact of load shedding on SA REIT prices.

4.4.2.3. Conclusion

The ADF test was conducted to ascertain the stationarity of the variables as required by the bounds test. The analysis revealed that RRT exhibits stationarity after first differencing, while LMWs remains stationary at level. Consequently, all variables were deemed suitable for inclusion in an ARDL bounds testing model. Using the AIC information criteria and employing the White's heteroskedasticity-consistent covariance matrix estimator, an optimal lag order of 1 was specified. Additionally, autocorrelation was also tested for in the regression and the results indicated positive evidence of autocorrelation. To rectify this issue, a one-period lagged variable of LRRT was introduced.

From the results of the bounds test, it can be concluded that there is no long-run relationship between SA REITS and Load shedding in the long-run.

The short run results indicated positive relationship; however, all the variables were insignificant, with p-values above the 5% significance level. The R-squared coefficient of 5.56% shows a poor fit and a weak relationship between the independent variables and the dependent variable. These results make it difficult for one to draw conclusions about the impact of load shedding to SA REIT prices.

The robustness test model was done where a bounds test was conducted to examine the long-run relationship between electricity supply and South African REIT prices using a new ARDL model. The model selection was based on AIC, and a trend component was included. Results showed that the lag of the dependent variable was significant, but both Electricity Supply and the constant were statistically insignificant, indicating no long-run relationship.

Although the model had a strong overall fit with the R-squared coefficient of 89.58% and passed residual diagnostics, the bounds test confirmed no cointegration, as the F-statistic was below the I(0) critical value. This suggests electricity supply does not have a significant long-term impact on REIT prices, potentially due to data limitations and omitted variables.

In the short-run model, all variables were also statistically insignificant with the R-squared coefficient of 0.0554, indicating a weak relationship and poor model fit. While there was a positive but insignificant relationship between LES and REIT prices, the low explanatory power makes it difficult to draw meaningful conclusions about the impact of load shedding on REIT performance.

4.5. APT Model

The secondary objective of this study is to identify the features of the underlying factor structure, particularly focusing on the relationship between REIT returns, which will be analysed through two REIT portfolios and the load-shedding variables. The assessment of the APT will be conducted using time series regression to estimate the beta coefficients and risk premia.

4.5.1. APT Diagnostic Test for existing variables

4.5.1.1. Correlation & Multicollinearity

Multicollinearity occurs when there is a strong or exact correlation between independent variables. This situation makes it challenging to obtain reliable estimates for the individual coefficients of those variables, potentially leading to inaccurate conclusions about the relationship between the dependent variable and the predictors.

Pearson's correlation coefficient is used to measure the strength of the association between two independent variables. As a general rule, multicollinearity is considered a significant issue when the correlation coefficient between two variables exceeds 0.8 or 0.9 (Gujarati, 2019; Hair et al., 2018).

Variables	LBCO	INF	LEXP	LGD_ZAR	GDP	LIMP	LJSE	LMS	LMWS	LZAR_USD
LBCO	1,0000									
INF	-0,3144	1,0000								
LEXP	0,5311	-0,1405	1,0000							
LGD_ZAR	0,1246	-0,0188	0,8084	1,0000						
GDP	0,5170	-0,0962	0,5649	0,1656	1,0000					
LIMP	0,3772	-0,0962	0,2815	0,0840	0,2966	1,0000				
LJSE	0,4968	-0,2610	0,8866	0,7158	0,4904	0,2976	1,0000			
LMS	-0,1523	0,0651	0,0979	0,2273	-0,1406	-0,9165	0,0440	1,0000		
LMWS	-0,1942	0,0805	0,2340	0,3371	-0,0935	-0,1700	0,1768	0,2772	1,0000	
LZAR_USD	0,3340	0,0494	0,3764	0,4022	-0,2064	0,2811	0,2811	0,0600	0,1036	1,0000

Table 25: Multicollinearity Results

Table 25 demonstrates a high positive correlation between LEXP and LGD_ZAR as well as LEXP and LJSE. The correlation between these variables is greater than 0.8, indicating a high possibility of multicollinearity.

4.5.1.2. Variance Inflation Factor

The VIF was conducted as a second test for multicollinearity. The VIF is a metric that quantifies the extent to which the variance of an estimated regression coefficient is inflated due to multicollinearity.

<table>
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<td>
<table>
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<tr><td>INF</td><td>1,2482</td></tr>
<tr><td>GDP</td><td>3,9761</td></tr>
<tr><td>LEXP</td><td>31,7991</td></tr>
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<tr><td>LIMP</td><td>137,9590</td></tr>
<tr><td>LJSE</td><td>6,0439</td></tr>
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<td>
<table>
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<tr><td>INF</td><td>1,9249</td></tr>
<tr><td>GDP</td><td>4,6929</td></tr>
<tr><td>LEXP</td><td>18,3492</td></tr>
<tr><td>LGD_ZAR</td><td>6,7556</td></tr>
<tr><td>LJSE</td><td>5,5437</td></tr>
<tr><td>LMS</td><td>1,1606</td></tr>
<tr><td>LMWS</td><td>1,8348</td></tr>
<tr><td>LZAR_USD</td><td>2,7652</td></tr>
</table>
</td>
<td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>LBCO_ZAR</td><td>2,5238</td></tr>
<tr><td>INF</td><td>1,8826</td></tr>
<tr><td>GDP</td><td>2,6501</td></tr>
<tr><td>LGD_ZAR</td><td>3,0869</td></tr>
<tr><td>LJSE</td><td>4,2921</td></tr>
<tr><td>LMS</td><td>1,1545</td></tr>
<tr><td>LMWS</td><td>1,6279</td></tr>
<tr><td>LZAR_USD</td><td>2,3622</td></tr>
</table>
</td>
</tr>
<tr>
<td>LIMP, LMS and LEXP have centered VIF results greater than 10, with LIMP having the highest centered VIF result was dropped and test was reconducted without the variable to test for improvement. The new results are shown in the second column.</td>
<td>The LIMP variable was dropped from the analysis due to having the highest centered VIF result. Omitting LIMP resulted in an enhancement of the LMS variable, which now produced results below 10.

LEXP also experienced improvement though, its value still greater 10, thus variable was dropped and a third round of centered VIF testing was conducted. The new results are shown in the third column.</td>
<td>After dropping the LIMP and LEXP variables due to having centered VIF result greater than 10, all the remaining variables now have centered VIF results that are less than 10. As a result, multicollinearity is eliminated in the regression.</td>
</tr>
</table>

Table 26: VIF Test Results

In Table 26, the first attempt shows that LMS, LEXP, LIMP and LMS have centered VIF values greater than 10, which implies that the regression coefficients are poorly estimated due to presence of multicollinearity. The removal of the LEXP and LIMP variables in the second and third attempts, respectively, resulted in the remaining variables having centered VIF values of less than 10, indicating the elimination of multicollinearity within the independent variables.

If not addressed, multicollinearity can lead to skewed or misleading results in the regression model. It can cause wider confidence intervals, resulting in less reliable estimates of the effect of independent variables.

4.5.2. Regression Results

In this section, empirical analysis is conducted to ascertain and comprehend the factors influencing the portfolio REIT Return. By employing the APT framework, the primary objective is to uncover the LMWs variable risk factors and their influence on REIT prices and returns, while also addressing the analysis of the remaining independent variable inputs.

The OLS method regression analysis was employed for the data analysis. The results were as follows:

		Portfolio A		**Portfolio B**	
	Variables	Coef.	Prob.	Coef.	Prob.
Sensitivity Results (β)	LMWS	-0,0457	0,3387	-0,013034	0,3419
	GDP_GROWTH	-0,0063	0,1814	0,0009	0,4820
	INF	0,0294	0,3434	-0,0037	0,6744
	LBCO_ZAR	-0,0614	0,2081	-0,0117	0,3991
	LGD_ZAR	-0,1552	0,2270	-0,0794	0,0340
	LJSE	0,2620	0,0392	0,0474	0,1875
	LMS	0,0382	0,0388	0,0035	0,5013
	LZAR_USD	-0,1814	0,1705	0,0964	0,0131
Risk Premia Results (λ)	C(1)	-0,0439	0,3731	0,0129	0,3478
	C(2)	-0,0153	0,1710	-0,0052	0,2712
	C(3)	0,0311	0,3127	0,0318	0,3204
	C(4)	-0,0717	0,1479	-0,0118	0,3984
	C(5)	-0,2050	0,1027	-0,0808	0,0322
	C(6)	0,2772	0,0319	0,0450	0,2165
	C(7)	0,0419	0,0247	0,0035	0,4977
	C(8)	-0,0366	0,5167	0,0941	0,0153
	R-squared	0,2238		0,1628	
	Adjusted R-squared	0,1082		0,0381	
	Durbin-Watson stat	2,1930		2,0814	

Table 27: APT Regression Results – Coef. = Coefficients, Prob. = Probability .
The first portion of the results presents the sensitivity of the eight macroeconomic variables, also known as risk factors, for Portfolio A and Portfolio B. A simultaneous regression analysis was conducted, and the betas derived from the sensitivity analysis were applied to the second portion of the regression to determine the risk premium results. The coefficients C(1),C(2),C(3), also referred to as lambdas, represent the risk premia derived from the sensitivity variables for Portfolio A and Portfolio B.

4.5.2.1. Results for Portfolio A

Sensitivity Results

The regression results in Table 27 found the beta value of LMWs for Portfolio A negative and statistically insignificant with REIT return as the p-value is greater than 5.00%. This indicates that the LMWs factor of portfolio A is not sensitive to the LMWs factor. LJSE and LMS are the only significant variables with p-values below 5.00% and both variables are positively related to portfolio A's return. The beta coefficients are less than 1 which means that these variables are negatively related but have a relatively small impact on the Portfolio A's returns. The remaining variables have insignificant beta values, with p-values greater than **0.05**. The differences in the returns of these portfolios are due to the varying share prices and characteristics of each company.

Risk Premia Results

The regression results for the lambda calculations found the risk premia for LMWs to be positive and statistically insignificant, with the p-value greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return. Only C(6) and C(7) variables, which are lambda variables derived from the LJSE and LMS betas, are significant, with p-values below 0.05. Both variables are positively related to Portfolio A's return. The risk premia are less than 1, indicating that these variables have a positive but relatively small impact on Portfolio A's returns.

The remaining variables have insignificant risk premia, with p-values greater than 0.05.

4.5.2.2. Results for Portfolio B

Sensitivity Results

The regression results found the beta value of LMWs for Portfolio B to be positive but statistically insignificant, with the REIT return's p-value greater than 0.05. This indicates that the LMWs factor of portfolio B is not sensitive to the LMWs factor. The regression analysis results show that LGD_ZAR and LZAR_USD are the only significant variables, with p-values below 0.05. The LGD_ZAR variable is negative, while the LZAR_USD variable is positively related to portfolio B's return. The beta coefficients are less than 1, meaning these variables have a relatively small impact on Portfolio B's returns.

The remaining variables have insignificant beta values, with p-values greater than 0.05. The overall fit of the model, as indicated by the R-squared and adjusted R-squared, is quite low, suggesting that the model does not explain much of the variability in Portfolio B's returns. These results confirm that the model has limited explanatory power, aligning with findings by Spyridisa et al. (2012) and Amtiran et al. (2017), who also found insignificant results when applying the APT model to their portfolios. Spyridisa et al. (2012) attributed some of their insignificant results to data limitations, specifically noting that the small sample size from the Athens Stock Exchange affected the results and led to their insignificance. Amtiran et al. (2017) attributed these insignificant results to the fact that not all relevant macroeconomic factors were included, and variations in data, research settings, and methodologies contributed to differing outcomes. Additionally, their study highlights that the APT model does not explicitly address the macroeconomic factors that most affect return rates, due to the interconnected nature of these factors.

Risk Premia Results

The regression results for the lambda calculations found the risk premia results of LMWs to be positive and statistically insignificant with REIT return, as the p-value is greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return.

Only the C(4) and C(8) variables, which are lambda variables derived from LGD_ZAR and LZAR_USD, are significant variables with p-values below 0.05. These variables are both positively related to Portfolio B's return. The risk premia are less than 1, meaning that these variables have a positive but relatively small impact on the Portfolio B's returns. The rest of the variables have insignificant risk premia, with p-values greater than 0.05.

The outcome of Portfolio A and B are similar.

4.5.3. VIF test results using LMWs with new variables

<table>
<tr><td colspan="3">VIF Test Result</td></tr>
<tr><td>1st attempt results</td><td>2nd attempt results – Variable is dropped</td><td>3rd attempt results – more variables dropped</td></tr>
<tr>
<td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>LMWS</td><td>1,9852</td></tr>
<tr><td>GDP</td><td>4,167</td></tr>
<tr><td>INF</td><td>1,8871</td></tr>
<tr><td>LBCO</td><td>3,9775</td></tr>
<tr><td>LGD_ZAR</td><td>10,5085</td></tr>
<tr><td>LIPI</td><td>1,8887</td></tr>
<tr><td>LJSE</td><td>9,6318</td></tr>
<tr><td>ZAR_USD</td><td>10,4164</td></tr>
<tr><td>LEXP</td><td>38,5593</td></tr>
<tr><td>LIMP</td><td>204,8858</td></tr>
<tr><td>LMS</td><td>187,308</td></tr>
<tr><td>COV</td><td>3,4088</td></tr>
</table>
</td>
<td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>LMWS</td><td>1,9245</td></tr>
<tr><td>GDP</td><td>3,9329</td></tr>
<tr><td>INF</td><td>1,8170</td></tr>
<tr><td>LBCO</td><td>3,9628</td></tr>
<tr><td>LGD_ZAR</td><td>10,3087</td></tr>
<tr><td>LIPI</td><td>1,8655</td></tr>
<tr><td>LJSE</td><td>9,5552</td></tr>
<tr><td>ZAR_USD</td><td>10,3122</td></tr>
<tr><td>LEXP</td><td>27,8023</td></tr>
<tr><td>COV</td><td>3,3165</td></tr>
</table>
</td>
<td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>LMWS</td><td>1,5612</td></tr>
<tr><td>GDP</td><td>1,3875</td></tr>
<tr><td>INF</td><td>1,5839</td></tr>
<tr><td>LBCO</td><td>2,3464</td></tr>
<tr><td>LIPI</td><td>1,3512</td></tr>
<tr><td>LJSE</td><td>2,1841</td></tr>
<tr><td>COV</td><td>1,8518</td></tr>
</table>
</td>
</tr>
<tr>
<td>LGD_ZAR, ZAR_USD, LEXP, LIMP and LMS have centered VIF results greater than 10. The LIMP and LMS variables were dropped and test was reconducted without the variable to test for improvement. The new results are shown in the second column.</td>
<td>After dropping those 2 variables due to having high centered VIF, LGD_ZAR, ZAR_USD and LEXP still had a centered VIF results that are greater than 10. The test was reconducted without these variables and the improved results are shown in the third column.</td>
<td>all the remaining variables now have centered VIF results that are less than 10. As a result, multicollinearity is eliminated in the regression.</td>
</tr>
</table>

Table 28:VIF Test Results

In Table 28, the first attempt shows that LGD_ZAR, ZAR_USD, LEXP, LIMP and LMS have centered VIF values greater than 10, which implies that the regression coefficients are poorly estimated due to presence of multicollinearity. The removal of these variables by the third attempts, resulted in the remaining variables having centered VIF values of less than 10, indicating the elimination of multicollinearity within the independent variables.

4.5.3.1. APT Regression Results - using LMWs with new variables

The primary objective is to uncover the LMWs variable risk factors and their influence on REIT prices and returns, while also addressing the analysis of the remaining independent variable inputs.

The OLS method regression analysis was employed for the data analysis. The results were as follows:

		Portfolio A		**Portfolio B**	
	Variables	Coef.	Prob.	Coef.	Prob.
Sensitivity Results (β)	LMWS	-0,0017	0,8926	-0,0706	0,1473
	GDP	0,0002	0,7484	-0,0018	0,4554
	INF	0,0155	0,0825	-0,0195	0,5721
	LBCO	0,0286	0,0457	0,0661	0,2350
	LIPI	-0,0035	0,9087	0,1212	0,3123
	LJSE	-0,0657	0,0255	0,1123	0,7369
	COV	0,0051	0,5037	0,0299	0,0356
Risk Premia Results (λ)	C(1)	-0,0009	0,4931	-0,0063	0,1814
	C(2)	0,0042	0,6345	-0,0294	0,3434
	C(3)	0,0118	0,3984	-0,0614	0,2081
	C(4)	0,0808	0,0322	0,1552	0,2270
	C(5)	-0,0450	0,2165	0,2620	0,0392
	C(6)	-0,0035	0,4977	0,0382	0,0388
	C(7)	0,0129	0,3478	0,0457	0,3387
	R-squared	0,1572		0,2238	
	Adjusted R-squared	0,0316		0,1082	
	Durbin Watson stat	1,5759		2,1930	

Table 29: table description is the same as table 27

In Table 29, the first attempt shows that LMS, LEXP, LIMP and LMS have centered VIF values greater than 10, which implies that the regression coefficients are poorly estimated due to presence of multicollinearity. The removal of the LEXP and LIMP variables in the second and third attempts, respectively, resulted in the remaining variables having centered VIF values of less than 10, indicating the elimination of multicollinearity within the independent variables.

4.5.4. Regression Results

In this section, empirical analysis is conducted to ascertain and comprehend the factors influencing the portfolio REIT Return. By employing the APT framework, the primary objective is to uncover the LMWs variable risk factors and their influence on REIT prices and returns, while also addressing the analysis of the remaining independent variable inputs.

The OLS method regression analysis was employed for the data analysis. The results were as follows:

		Portfolio A		Portfolio B	
	Variables	Coef.	Prob.	Coef.	Prob.
Sensitivity Results	LMWS	-0,0017	0,8926	-0,0706	0,1473
	GDP	0,0002	0,7484	-0,0018	0,4554
	INF	0,0155	0,0825	-0,0195	0,5721
	LBCO	0,0286	0,0457	0,0661	0,2350
	LIPI	-0,0035	0,9087	0,1212	0,3123
	LJSE	-0,0657	0,0255	0,1123	0,7369
	COV	0,0051	0,5037	0,0299	0,0356
Risk Premia Results (λ)	C(1)	-0,0009	0,4931	-0,0063	0,1814
	C(2)	0,0042	0,6345	-0,0294	0,3434
	C(3)	0,0118	0,3984	-0,0614	0,2081
	C(4)	0,0808	0,0322	0,1552	0,2270
	C(5)	-0,0450	0,2165	0,2620	0,0392
	C(6)	-0,0035	0,4977	0,0382	0,0388
	C(7)	0,0129	0,3478	0,0457	0,3387
	R-squared	0,1572		0,2238	
	Adjusted R-squared	0,0316		0,1082	
	Durbin Watson stat	1,5759		2,1930	

Table 30: table description same as table 27

4.5.4.1. Results for Portfolio A

Sensitivity Results

The regression results in Table 30 found the beta value of LMWs for Portfolio A negative and statistically insignificant with REIT return as the p-value is greater than 5.00%. This indicates that the LMWs factor of portfolio A is not sensitive to the LMWs factor. The LBCO and LJSE are the only significant variables with p-values below 0.05%. The LBCO variable is positively related to portfolio A’s return while LJSE is negative. The beta coefficients are less than 1 which means that these variables are negatively related but have a relatively small impact on the Portfolio A's returns. The remaining variables have insignificant beta values, with p-values greater than 0.05. The differences in the returns of these portfolios are due to the varying share prices and characteristics of each company.

The remaining variables have insignificant beta values, with p-values greater than 0.05. The overall fit of the model, as indicated by the R-squared and adjusted R-squared, is quite low, suggesting that the model does not explain much of the variability in Portfolio A’s returns.

Risk Premia Results

The regression results for the lambda calculations found the risk premia for LMWs to be positive and statistically insignificant, with the p-value greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return. Only C(4) variable which is lambda variable derived from the LBCO beta, is significant, with p-values below 0.05. The variable is positively related to Portfolio A's return. The risk premia are less than 1, indicating that these variables have a positive but relatively small impact on Portfolio A's returns.

The remaining variables have insignificant risk premia, with p-values greater than 0.05.

4.5.4.2. Results for Portfolio B

Sensitivity Results

The regression results found the beta value of LMWs for Portfolio B to be negative and statistically insignificant, with the REIT return's p-value greater than 0.05. This indicates that the LMWs factor of portfolio B is not sensitive to the LMWs factor. The regression analysis results show that only COV is a significant variable, with p-values below 0.05. COV variable is also positively related to portfolio B's return. The beta coefficients are less than 1, meaning these variables have a relatively small impact on Portfolio B's returns.

The remaining variables have insignificant beta values, with p-values greater than 0.05. The overall fit of the model, as indicated by the R-squared and adjusted R-squared, is quite low, suggesting that the model does not explain much of the variability in Portfolio B's returns.

Risk Premia Results

The regression results for the lambda calculations found the risk premia results of LMWs to be positive and statistically insignificant with REIT return, as the p-value is greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return.

Only the C(4), C(6) and C(7) variables, which are lambda variables derived from LIPI, LJSE and COV, are significant variables with p-values below 0.05. The variables are positively related to Portfolio B's return. The risk premia are less than 1, meaning that these variables have a positive but relatively small impact on the Portfolio B's returns. The rest of the variables have insignificant risk premia, with p-values greater than 0.05.

The outcome of Portfolio A and B are similar.

4.5.5. VIF test results using LES with existing variables

<table>
<tr><td colspan="3">VIF Test Result</td></tr>
<tr><td>1st attempt results</td><td>2nd attempt results – Variable is dropped</td><td>3rd attempt results – more variables dropped</td></tr>
<tr><td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>COV</td><td>3,4089</td></tr>
<tr><td>GDP</td><td>4,3276</td></tr>
<tr><td>INF</td><td>1,8872</td></tr>
<tr><td>LBCO</td><td>4,3662</td></tr>
<tr><td>LES</td><td>3,8331</td></tr>
<tr><td>LEXP</td><td>38,7949</td></tr>
<tr><td>LGD_ZAR</td><td>11,0681</td></tr>
<tr><td>LIMP</td><td>220,2352</td></tr>
<tr><td>LIPI</td><td>1,8890</td></tr>
<tr><td>LJSE</td><td>10,5216</td></tr>
<tr><td>LMS</td><td>204,6904</td></tr>
<tr><td>ZAR_USD</td><td>10,9318</td></tr>
</table>
</td><td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>COV</td><td>2,3634</td></tr>
<tr><td>GDP</td><td>3,6045</td></tr>
<tr><td>INF</td><td>1,3599</td></tr>
<tr><td>LBCO</td><td>3,1959</td></tr>
<tr><td>LES</td><td>2,4531</td></tr>
<tr><td>LEXP</td><td>20,4631</td></tr>
<tr><td>LGD_ZAR</td><td>9,6987</td></tr>
<tr><td>LIPI</td><td>1,7694</td></tr>
<tr><td>LJSE</td><td>5,96158</td></tr>
<tr><td>LZAR_USD</td><td>3,2632</td></tr>
</table>
</td><td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>COV</td><td>2,7281</td></tr>
<tr><td>GDP</td><td>2,3333</td></tr>
<tr><td>INF</td><td>1,3344</td></tr>
<tr><td>LBCO</td><td>2,3866</td></tr>
<tr><td>LES</td><td>2,4364</td></tr>
<tr><td>LGD_ZAR</td><td>5,2406</td></tr>
<tr><td>LIPI</td><td>1,6392</td></tr>
<tr><td>LJSE</td><td>4,1848</td></tr>
<tr><td>LZAR_USD</td><td>2,9697</td></tr>
</table>
</td></tr>
<tr><td>LEXP, LGD_ZAR, LIMP, LJSE, LMS and ZAR_USD have centered VIF results greater than 10. The LIMP and LMS variables were dropped and the test was reconducted without the variable to test for improvement. The new results are shown in the second column.</td><td>After dropping those 2 variables due to having high centered VIF, LGD_ZAR and LJSE improved and centered VIF results are below 10. LEXP still had a centered VIF results that are greater than 10. The test was reconducted without LEXP variable.</td><td>Improved results are shown in the third column. All the remaining variables now have centered VIF results that are less than 10. As a result, multicollinearity is eliminated in the regression.</td></tr>
</table>

Table 31: VIF Test Results

In Table 31, the first attempt shows that LEXP, LGD_ZAR, LIMP, LJSE, LMS and ZAR_USD have centered VIF values greater than 10, which implies that the regression coefficients are poorly estimated due to presence of multicollinearity. The removal of LIMP, LMS and LEXP variables by the third attempts, resulted in the remaining variables having centered VIF values of less than 10, indicating the elimination of multicollinearity within the independent variables.

4.5.5.1. APT Regression Results - using LMWs with new variables

Empirical analysis is conducted to ascertain and comprehend the factors influencing the portfolio REIT Return. By employing the APT framework, the primary objective is to uncover the LES variable risk factors and their influence on REIT prices and returns, while also addressing the analysis of the remaining independent variable inputs.

The OLS method regression analysis was employed for the data analysis. The results were as follows:`

		Portfolio A		**Portfolio B**	
	Variables	Coef	Prob.	Coef.	Prob.
	COV	0,0149	0,0799	0,0314	0,4088
Sensitivity	GDP	0,0008	0,3441	0,0000	0,9939
Results (β)	INF	0,0054	0,4535	-0,0310	0,3465
	LBCO	0,0084	0,5659	0,1309	0,0539
	LES	-0,0788	0,0512	-0,0248	0,8902
	LGD_ZAR	-0,0646	0,2472	0,2926	0,2484
	LIPI	0,0227	0,4750	0,0984	0,4945
	LJSE	-0,1274	0,0041	-0,0240	0,9007
	LZAR_USD	0,0995	0,0372	-0,1521	0,4733
	LEXP	0,1017	0,0852	-0,2772	0,2965
	C(1)	-0,0063	0,1814	0,0009	0,4820
	C(2)	0,0294	0,3434	-0,0037	0,6744
Risk	C(3)	-0,0614	0,2081	-0,0117	0,3991
Premia	C(4)	-0,1552	0,2270	-0,0794	0,0340
Results (λ)	C(5)	0,2620	0,0392	0,0474	0,1875
	C(6)	0,0382	0,0388	0,0035	0,5013
	C(7)	-0,0457	0,3387	0,0130	0,3419
	C(8)	-0,1814	0,1705	0,0964	0,0131
	C(9)	-0,0117	0,3991	-0,0118	0,3984
R-squared		0,2238		0,1628	
Adjusted R-squared		0,1082		0,0381	
Durbin Watson stat		2,1930		1,5814	

Table 22: APT Regression Results – Coef. = Coefficients, Prob. = Probability .
The first portion of the results presents the sensitivity of the eight macroeconomic variables, also known as risk factors, for Portfolio A and Portfolio B. A simultaneous regression analysis was conducted, and the betas derived from the sensitivity analysis were applied to the second portion of the regression to determine the risk premium results. The coefficients

C(1),C(2),C(3), also referred to as lambdas, represent the risk premia derived from the sensitivity variables for Portfolio A and Portfolio B.

4.5.1.4.2. Results for Portfolio A

Sensitivity Results

The regression results in Table 22 found the beta value of LES for Portfolio A negative and statistically insignificant with REIT return as the p-value is greater than 0.05. This indicates that the LES factor of portfolio A is not sensitive to independent factor. Five variables are significant, COV, GDP, LBCO, LIPI and INF, with p-values below 0.05 and all of them are positively related to portfolio A's return. The beta coefficients are less than 1 which means that these variables are negatively related but have a relatively small impact on the Portfolio A's returns. The remaining variables have insignificant beta values, with p-values greater than 0.05. The differences in the returns of these portfolios are due to the varying share prices and characteristics of each company.

The overall fit of the model, as indicated by the R-squared and adjusted R-squared are low, suggesting that the model does not explain much of the variability in Portfolio A's returns.

Risk Premia Results

The regression results for the lambda calculations found the risk premia for LES to be negitive and statistically insignificant, with the p-value greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return. C(1), C(6), C(7) and C(9) variables derived from COV, LGD_ZAR, LIPI and LEXP risk premia results are significant, with p-values below 0.05. of those variables, C(1), C(7) and C(9) are negatively related to Portfolio A's return. The risk premia are less than 1, indicating that these variables have a negative but relatively small impact on Portfolio A's returns.

The remaining variables have insignificant risk premia, with p-values greater than 0.05.

Results for Portfolio B

Sensitivity Results

The regression results found the beta value of LES for Portfolio B to be negative and statistically insignificant, with the REIT return's p-value greater than 0.05. This indicates that the LES factor of portfolio B is not sensitive to the independent factor. The regression analysis results show that none of the variables are significant with p-values above 0.05. The beta coefficients are less than 1, meaning these variables have a relatively small impact on Portfolio B's returns.

Risk Premia Results

The regression results for the lambda calculations found the risk premia results of LES to be positive and statistically insignificant with REIT return, as the p-value is greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return.

Only C(4) and C(8) variables, which are lambda variables derived from LBCO and LZAR_USD, are significant variables with p-values below 0.05. The variables are positively related to Portfolio B's return. The risk premia are less than 1, meaning that these variables have a positive but relatively small impact on the Portfolio B's returns. The rest of the variables have insignificant risk premia, with p-values greater than 0.05.

The overall fit of the model, as indicated by the R-squared and adjusted R-squared, is quite low, suggesting that the model does not explain much of the variability in Portfolio B's returns.

The outcome of Portfolio A and B are similar.

4.5.1.5. VIF test results using LES with new variables

<table>
<tr><td colspan="3">VIF Test Result</td></tr>
<tr><td>1st attempt results</td><td>2nd attempt results – Variable is dropped</td><td>3rd attempt results – more variables dropped</td></tr>
<tr>
<td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>COV</td><td>3,3800</td></tr>
<tr><td>GDP</td><td>4,0933</td></tr>
<tr><td>INF</td><td>1,6160</td></tr>
<tr><td>LBCO</td><td>3,6887</td></tr>
<tr><td>LCPI</td><td>53,8158</td></tr>
<tr><td>LES</td><td>2,9735</td></tr>
<tr><td>LEXP</td><td>36,4734</td></tr>
<tr><td>LGD_ZAR</td><td>10,9541</td></tr>
<tr><td>LIMP</td><td>213,7555</td></tr>
<tr><td>LIPI</td><td>1,8909</td></tr>
<tr><td>LJSE</td><td>10,1402</td></tr>
<tr><td>LMS</td><td>196,4913</td></tr>
<tr><td>ZAR_USD</td><td>10,3638</td></tr>
</table>
</td>
<td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>COV</td><td>1,7976</td></tr>
<tr><td>GDP</td><td>1,5550</td></tr>
<tr><td>INF</td><td>1,1388</td></tr>
<tr><td>LBCO</td><td>1,8740</td></tr>
<tr><td>LES</td><td>1,4284</td></tr>
<tr><td>LIPI</td><td>1,3372</td></tr>
<tr><td>LEXP</td><td>35,2158</td></tr>
<tr><td>LGD_ZAR</td><td>10,5541</td></tr>
<tr><td>LJSE</td><td>10,0002</td></tr>
<tr><td>ZAR_USD</td><td>10,1238</td></tr>
</table>
</td>
<td>
<table>
<tr><th>Variables</th><th>Centered VIF</th></tr>
<tr><td>COV</td><td>1,7976</td></tr>
<tr><td>GDP</td><td>1,5550</td></tr>
<tr><td>INF</td><td>1,1388</td></tr>
<tr><td>LBCO</td><td>1,8740</td></tr>
<tr><td>LES</td><td>1,4284</td></tr>
<tr><td>LIPI</td><td>1,3372</td></tr>
</table>
</td>
</tr>
<tr>
<td>LEXP, LGD_ZAR, LIMP, LJSE, LMS and ZAR_USD have centered VIF results greater than 10. The LIMP and LMS variables were dropped and the test was reconducted without those variables to test for improvement. The new results are shown in the second column.</td>
<td>After dropping those 2 variables due to having high centered VIF, there was still not much improvement on the remaining variables as a result LEXP, LGD_ZAR, LJSE and ZAR_USD were removed in the 3rd attempt due to centered VIF results that are greater than 10.</td>
<td>Improved results are shown in the third column. All the remaining variables now have centered VIF results that are less than 10. As a result, multicollinearity is eliminated in the regression.</td>
</tr>
</table>

In Table 24, the first attempt shows that LEXP, LGD_ZAR, LIMP, LJSE, LMS and ZAR_USD have centered VIF values greater than 10, which implies that the regression coefficients are poorly estimated due to presence of multicollinearity. The removal of LIMP, LMS, LEXP, LGD_ZAR, LJSE AND ZAR_USD variables by the third attempts, resulted in the remaining variables having centered VIF values of less than 10, indicating the elimination of multicollinearity within the independent variables.

4.5.2. APT Regression Results - using LES with new variables

Empirical analysis is conducted to ascertain and comprehend the factors influencing the portfolio REIT Return. By employing the APT framework, the primary objective is to uncover the LES variable risk factors and their influence on REIT prices and returns, while also addressing the analysis of the remaining independent variable inputs.

The OLS method regression analysis was employed for the data analysis. The results were as follows:`

		Portfolio A		**Portfolio B**	
	Variables	Coef	Prob.	Coef.	Prob.
Sensitivity Results (β)	COV	0,0040	0,6020	0,0553	0,0725
	GDP	0,0004	0,5815	-0,0013	0,6298
	INF	0,0180	0,0216	-0,0377	0,2134
	LBCO	0,0149	0,2456	0,0598	0,2402
	LES	-0,0690	0,0462	-0,0780	0,5622
	LIPI	-0,0090	0,7700	0,0996	0,4224
Risk Premia Results (λ)	C(1)	-0,0064	0,1710	-0,0052	0,2712
	C(2)	0,0311	0,3127	0,0318	0,3204
	C(3)	-0,0657	0,1766	-0,0717	0,1479
	C(4)	-0,1469	0,2498	-0,2050	0,1027
	C(5)	0,2788	0,0290	0,2772	0,0319
	C(6)	0,0371	0,0432	0,0419	0,0247
R-squared		0,2368		0,1995	
Adjusted R-squared		0,1231		0,0802	
Durbin Watson stat		2,2055		2,1511	

Table 23: APT Regression Results – Coef. = Coefficients, Prob. = Probability .

The first portion of the results presents the sensitivity of the eight macroeconomic variables, also known as risk factors, for Portfolio A and Portfolio B. A simultaneous regression analysis was conducted, and the betas derived from the sensitivity analysis were applied to the second portion of the regression to determine the risk premium results. The coefficients C(1),C(2),C(3), also referred to as lambdas, represent the risk premia derived from the sensitivity variables for Portfolio A and Portfolio B.

4.5.2.4. Results for Portfolio A

Sensitivity Results

The regression results in Table 23 found the beta value of LES for Portfolio A negative and statistically insignificant with REIT return as the p-value is greater than 0.05. This indicates that the LES factor of portfolio A is not sensitive to independent factor. All the other variables are significant with p-values below 0.05. LIPI is the only negative variable in portfolio A. The beta coefficients are less than 1 which means that these variables are negatively related but have a relatively small impact on the Portfolio A's returns.

The overall fit of the model, as indicated by the R-squared and adjusted R-squared are low, suggesting that the model does not explain much of the variability in Portfolio A's returns.

Risk Premia Results

The regression results for the lambda calculations found the risk premia for LES to be negative and statistically insignificant, with the p-value greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return. C(1), C(2) and C(6) variables derived from COV, GDP and LIPI risk premia results are significant, with p-values below 0.05. of those variables, only C(1) is negatively related to Portfolio A's return. The risk premia are less than 1, indicating that these variables have a negative but relatively small impact on Portfolio A's returns.

The remaining variables have insignificant risk premia, with p-values greater than 0.05.

4.5.2.5. Results for Portfolio B

Sensitivity Results

The regression results found the beta value of LES for Portfolio B to be negative and statistically insignificant, with the REIT return's p-value greater than 0.05. This indicates that the LES factor of portfolio B is not sensitive to the independent factor. The regression analysis results show that none of the variables are significant with p-values above 0.05. The beta coefficients are less than 1, meaning these variables have a relatively small impact on Portfolio B's returns.

Risk Premia Results

The regression results for the lambda calculations found the risk premia results of LES to be positive and statistically insignificant with REIT return, as the p-value is greater than 0.05. This means that the risk premium does not have a statistically significant impact on the REIT return.

Only C(5) and C(6) variables, which are lambda variables derived from LES and LIPI, are significant variables with p-values below 0.05. The variables are positively related to Portfolio B’s return. The risk premia are less than 1, meaning that these variables have a positive but relatively small impact on the Portfolio B's returns. The rest of the variables have insignificant risk premia, with p-values greater than 0.05.

The overall fit of the model, as indicated by the R-squared and adjusted R-squared, is quite low, suggesting that the model does not explain much of the variability in Portfolio B’s returns.

The outcome of Portfolio A and B are similar.

4.5.3. Results Analysis

The outcomes of the APT model are consistent with the ARDL results presented in Section 4.1.1.1. The analysis reveals that there is no cointegration in the long-run relationship, indicating an absence of a long-term connection. In the short run, the results also demonstrate that the relationship between the MWs and RRT variables is insignificant, with p-values exceeding the 5% significance level. Within the APT model, most variables in the regression are insignificant for both Portfolio A and Portfolio B, except for LJSE and LMS in Portfolio A and LGD_ZAR and LZAR_USD in Portfolio B.

The purpose of the study was to determine the risk premia of the macroeconomic variables on the REIT return, with a primary focus on the load shedding variable (LMWs). Although the LMWs variable was insignificant in both Portfolio A and Portfolio B, the negative results in both regressions were anticipated as the relationship with the REIT portfolios supports Anderson and Dalgaard's (2013) assertion, discussed in the literature review, section 2.7, that inconsistent electricity supply impedes economic advancement, hindering a country's progress and development potential.

It is worth noting that the LMWs coefficients are close to 0, indicating a weak sensitivity to REIT returns. Furthermore, the weak relationship with the market-wide portfolio implies that other factors beyond market movements are likely driving the asset's returns. Investors should consider factors other than just LMWs performance when assessing the risk and return potential of Portfolio A and Portfolio B. The more significant variables in Portfolio A were LJSE and LMS, and in Portfolio B, the significant variables were LGD_ZAR and LZAR_USD.

The results of LMS having a significantly positive effect on Portfolio A were anticipated as the central bank increases the money supply, it injects liquidity into the financial system. This typically lowers interest rates, making borrowing cheaper for businesses and consumers. Lower interest rates reduce the cost of capital for companies, potentially boosting investment and profitability (Bredin et al., 2001). This can lead to higher returns as investors anticipate improved future earnings and economic conditions.

The results of LJSE having a significantly positive effect on Portfolio A’s return are consistent with the research conducted by Bhowmik and Wang (2020), which explores the pivotal role of stock markets in economic activities and highlights the correlation between market trends and portfolio performance. An increase in the JSE All Share Index has a positive impact on Portfolio A’s return. When the index increases, it generally indicates a rise in the overall market value of these companies; as a result, REITs are likely to benefit from the overall market uptrend. As the value of the underlying assets in the portfolio increases, so does the portfolio's return.

A robustness test was also conducted using 3 various models, which are:

1. APT model with MWs variable plus New Variables;
2. APT model with ES variable plus the existing variables;
3. APT model with ES variable plus New Variables.

The regression outcomes show that both LMWs and LES variables were statistically insignificant in influencing REIT returns across both Portfolio A and Portfolio B, suggesting they do not serve as strong explanatory risk factors for REIT performance in this context.

However, a few macroeconomic variables showed statistical significance in select portfolios:

For Portfolio A, variables like LBCO and LJSE were significant in the LMWs model, while COV, GDP, LBCO, LIPI, and INF were significant in the LES model.

For Portfolio B, COV was the only significant factor in the LMWs model, and LBCO and ZAR/USD showed significance in the LES model.

In terms of risk premia, most variables remained statistically insignificant. Only a few variables—such as C(4), C(6), and C(7) in some models—showed significant positive or negative impacts, but these effects were relatively small (coefficients < 1), implying limited influence on REIT returns.

The R-squared values across models were low, indicating that the macroeconomic variables included, even after adjusting for multicollinearity, explained only a small portion of the variability in REIT returns. This suggests that REIT performance may be driven by other factors not captured in the models, such as firm-specific variables, investor sentiment, or market microstructure dynamics.

The study concludes that while certain macroeconomic factors do exert some influence, LMWs and LES alone are not significant drivers of REIT returns in the South African context. Future research could benefit from incorporating additional or alternative variables, including microeconomic and behavioural indicators, to develop a more comprehensive understanding of REIT performance determinants.

South Africa’s money supply is regulated and managed by the SARB, which aims to maintain price stability through its inflation-targeting framework. Monetary policy is how the central bank manages the money supply to achieve its goals. The primary objective of monetary policy is to guide the economy by adjusting the money supply to achieve desired economic outcomes. To manage inflation, the SARB adjusts interest rates, striving to protect the value of the rand and ensure that consumer price inflation remains within the target range of 3% to 6% (South African Reserve Bank).

In May 2023, the SARB last adjusted the repo rate in response to inflation, which stood at 5.2% at that time (South African Government News Agency, 2024). The global context further complicates inflation management. During the early stages of the COVID-19 pandemic, global inflation sharply declined due to a substantial reduction in demand and a collapse in oil prices. However, by mid-2020, inflation began to rise again as demand recovered, supply chain disruptions persisted, and oil prices rebounded. By July 2022, global inflation had reached its highest level since the mid-1990s (Ha et al., 2024). Although there has been a subsequent decline, inflation remains significantly above pre-pandemic levels and is consequently impacting South Africa.

The result of the LGD_ZAR being negatively significant to Portfolio B was anticipated. Baur and McDermott (2016) and Akhtaruzzaman (2021) explain that gold is often viewed as a safe-haven asset, particularly during times of economic uncertainty or market volatility. According to Baur and McDermott (2010), since the beginning of the financial crisis in July 2007, the nominal gold price has risen by 42%. This is because, according to Gorton and Rouwenhorst (2006), gold often performs well during inflationary periods or when traditional financial markets are underperforming. When investors are concerned about the stability of financial markets or anticipate economic downturns, they may shift their investments from riskier assets like stocks and REITs to gold. This capital flight can lead to a decrease in demand for REITs, causing their prices and returns to fall. As a result, the outcome in this regression was anticipated.

Gold prices surged significantly in 2020, reaching record highs. The price of gold peaked at over $2,000 per ounce in August 2020, driven by the COVID-19 pandemic, economic uncertainty, and aggressive monetary stimulus measures by central banks (Bloomberg, 2020). The COVID-19 pandemic led to unprecedented economic disruptions and uncertainty, pushing investors towards gold as a safe-haven asset.

In contrast, the REIT market during the 2020 COVID-19 pandemic was negatively affected due to widespread economic disruptions, including lockdowns, changes in consumer behaviour, and significant disruptions to the real estate market. According to a report by NAREIT (2020), the FTSE NAREIT All Equity REITs Index dropped by over 30% from February to March 2020. This decline was driven by fears of rental income losses, particularly in sectors like retail and hospitality, which were severely impacted by lockdowns and reduced consumer activity (NAREIT, 2020).

The results showing that LZAR_USD has a significantly positive effect on Portfolio A are consistent with the findings of Li and Zhu (2022). Two of the leading causes of currency depreciation are an easy monetary policy and high inflation. When central banks implement low-interest-rate policies, there is an increase in liquidity as capital flows into assets offering higher yields. This influx of capital can lead to significant depreciation of the currency due to changes in interest rate differentials and investor behaviour (Mishkin, 2019; Frankel, 2021). Lower inflation can lead to lower interest rates, which benefits REITs by reducing borrowing costs, thereby increasing profitability and cash flow.

Political instability can also lead to currency depreciation. In South Africa, the currency is known for its volatility. It transitioned from the South African pound to the rand in 1961, with a conversion rate of 2 rand to 1 pound. Since September 11, 2013, the rand has depreciated against the US dollar at an annualized rate of 6.67%, exceeding South Africa's average inflation rate of 5.17% during the same period (IMF, 2024). Before former President Jacob Zuma’s appointment in May 2009, the rand/dollar exchange rate was relatively stable at R7.88. However, during Zuma’s tenure, particularly amid state capture allegations, the rand's value dropped to R11.69 by February 2018, marking a 48.35% depreciation (South African Reserve Bank, 2023). According to Kelly (2023) in Moneyweb, the volatility of the rand was exacerbated by the country’s state capture, depleting public funds through corrupt practices and embezzlement, resulting in economic stagnation and diminished investor confidence.

Since President Ramaphosa’s tenure, the rand has lost 41% of its value. When Ramaphosa was elected as president, there was initial market optimism reflected in the strengthening of the rand from R14.47 against the US dollar in November 2017 to R11.55, a phenomenon referred to as “Ramaphoria” (Greyling, 2023). However, Greyling (2023) explains that this enthusiasm was short-lived due to persistent challenges such as high unemployment, load shedding, inadequate infrastructure maintenance, high crime rates, and the collapse of municipal services. These factors have directly impacted stock price performance as well as the REIT market.

The results of this study indicate that the APT model does not explicitly account for the macroeconomic factors that most influence the rate of return, highlighting their interrelationships (Amtiran et al., 2017). Macroeconomic variables are intricately connected, forming a complex web of cause-and-effect relationships that shape the overall economic environment. These interrelationships mean that changes in one factor can influence others, impacting variables such as inflation, interest rates, and economic growth, which in turn affect the rate of return. Based on macroeconomic research, investors will invest in a country if it has stable macroeconomic conditions.

4.5.4. Conclusion

The multicollinearity test was conducted to assess for correlation, and the results revealed high positive correlation between LEXP and LGD_ZAR, as well as between LEXP and LJSE. This resulted in further testing using the centered VIF (Variance Inflation Factor) test. Ultimately, this led to the removal of the LIMP and LEXP variables, as their centered VIF results were greater than 10. The removal of these variables corrected the multicollinearity issue in the model.

After running the APT test, the results showed a low R-squared coefficient for both Portfolio A and Portfolio B in both the time series regression and cross-correlation regression, indicating a poor model fit between the independent and dependent variables. The variables that were statistically significant in the cross-sectional regression, at the 5% level, were LJSE and LMS for Portfolio A, and LGD_ZAR and LZAR_US for Portfolio B. The remaining variables were insignificant, with p-values greater than 5%.

The results of the LMWs coefficient were negative in both Portfolio A and Portfolio B and close to 0, indicating weak sensitivity and risk premia on REIT returns. Furthermore, the LMWs in both portfolios were statistically insignificant. Therefore, when the Megawatt shed decreases, LRRT tends to have slightly positive returns; however, the magnitude of this effect is relatively small due to the low coefficient. In fact, the impact is nearly negligible.

5. Summary, Conclusion and Recommendations

5.1. Introduction

This chapter provides an overview of the core findings of the research and offers recommendations for both current and future studies in the field. These recommendations are based on the conclusions drawn from the research and are intended to address the research problem and objectives effectively. Additionally, the chapter highlights areas that may benefit from further investigation and in-depth analysis.

5.2. Summary and Conclusion

This research study was carried out to achieve three primary objectives:

1. Determine if load shedding impacts South African REIT returns.
2. Assess the future impact of load shedding on South African REIT returns.
3. Identify the channels through which load shedding may affect REIT returns.

For the first objective, time series data from South Africa spanning April 2019 to December 2023 was analysed using the ARDL technique. The analysis revealed no long-run relationship between load shedding and REIT Returns. In the short run, the coefficient for LMWs was positive, indicating a direct relationship where increased megawatts released by Eskom generally lead to higher REIT prices. Conversely, higher load shedding stages, resulting from Eskom's grid megawatt cuts, negatively impact REIT prices. However, this positive relationship was statistically insignificant (with a p-value > 0.05), suggesting insufficient evidence to establish a significant relationship. Additionally, the R-squared value of 5.56% indicated that only a small portion of the variability in LRRT could be explained by LMWs, implying that the model may not be well-suited for the data and that more explanatory variables might be needed for a better understanding.

The second objective was to evaluate the future impact, if any, of load shedding on South African REIT returns. Results from the APT model indicated that LMWs in both Portfolio A and Portfolio B were insignificant, with negative coefficients close to 0. This suggests that LMWs do not explain the variation in South African REIT returns and therefore have a minimal future impact.

For the third objective, which was to identify the channels through which load shedding may affect REIT returns, both the ARDL and APT tests were employed. However, due to limitations inherent in these tests, the results were inconclusive. Despite this, there is potential for further research to improve understanding by incorporating additional macroeconomic variables and extending the study period. These adjustments could enhance the models' ability to reveal the extent of load shedding's impact on REIT returns in the long run.

5.3 Recommendation

This research contributes to the ARDL literature in the REIT market. However, the impact of load shedding was only observed for a very short period of time in South Africa and only one variable was used as a main component to assess its relationship with REIT Returns. Therefore, the research methodology warrants further examination to assess its suitability for addressing the main topic: the impact of load shedding on REIT returns. One recommendation for future research is to extend the data series, possibly from the inception of load shedding in South Africa to the present day, as the issue continues to be relevant.

Additionally, employing more sophisticated econometric techniques and models could enhance the accuracy of the results. Techniques such as dynamic panel data models (Arellano & Bover, 1995) and structural equation modelling (Bollen, 1989) may better capture the complex relationships and interactions between macroeconomic factors and REIT returns. These advanced methods could uncover subtle effects that simpler models might miss (Wooldridge, 2010; Chen, 2018).

Investigating the impact of load shedding on REIT returns across different sectors could also provide valuable insight. Sector-specific studies might reveal how various types of REITs (e.g., retail, office, industrial) respond differently to macroeconomic shocks. The methodology used by Akinsomi (2020) to assess the resilience of REITs during the pandemic could be replicated to evaluate the effects of load shedding on REITs.

In February 2024, during the SONA Address, President Cyril Ramaphosa remarked: "We have delivered on our commitments to bring substantial new power through private investment onto the grid, which is already helping to reduce load shedding. Last year, we implemented a major debt relief package which will enable Eskom to make investments in maintenance and transmission infrastructure and ensure its sustainability going forward… Through all these actions, we are confident that the worst is behind us and the end of load shedding is finally within reach.” Should the issue of load shedding be resolved in the near future, further research will still be necessary to estimate the long-term damage caused by load shedding to the REIT market and the South African economy as a whole.

Addressing these recommendations will enable future research to build upon the current study's findings, offering a more comprehensive understanding of the complex interactions between macroeconomic factors and REIT performance. This will contribute to more informed investment strategies and policy decisions, ultimately enhancing the resilience and stability of financial markets.

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