TOWARDS THE DEVELOPMENT OF A PREDICTIVE RENT MODEL IN NIGERIA AND SOUTH AFRICA

BY

OLADEJI JONATHAN DAMILOLA
17046701

THESIS PRESENTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR A MASTERS DEGREE OF REAL ESTATE AT THE UNIVERSITY OF PRETORIA

SUPERVISOR: PROF. KEVIN WALL
CO-SUPERVISOR: DR. JOSEPH AWOAMIM YACIM

SEPTEMBER 2019

DECLARATION

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously, in its entirety or in part, submitted it at any university for a degree.

Signature: Oladeji Jonathan Damilola

Date: 06/10/2019

ACKNOWLEDGEMENTS

My special appreciation goes to Dr. Joseph Yacim, without whom I would have been unable to complete this project. God's mercy and grace through him has made this possible. My gratitude is also extended to Dr. Douw Boshoff who facilitated my acceptance to the Real Estate Masters programme at the University of Pretoria and supported me until his resignation and to Prof. Kevin Wall for assisting as my new supervisor despite the limitations and the unprecedented situation.

Thanks to the partial grants from the African Real Estate Society, the financial burden of three years at the University did not weigh too heavily on me. At the same time I appreciate the support of strangers from all over the world who supported my work as a digital content writer. Those sales, the patronage and the voluntary donations helped me through financing this research and training.

I am grateful to Rachel Onamusi, Jane Oma, Drs. Kehinde and Ezekiel Omotosho, Mr. and Mrs. Idowu, Mrs. Ade Akinlaja, Monica Kunzekweguta and many others who continued to pray, support and counsel me. I am indeed a product of community, love and faith.

Not the least, my family has been a huge support in the persons of Engr. Oriyomi and Dr. Adenike Oladeji, David Oladeji, Eunice Oladeji and Deborah Oladeji. Finally, I am thankful to God and to the University of Pretoria for this opportunity to advance this research.

ABSTRACT

This research aimed to identify reliable economic data for predictive rent modelling in South Africa and Nigeria, as a contribution towards the growing debate on real estate rental forecasting from the African perspective. The data were obtained from the Iress Expert Database, Stat SA, the Central Bank of Nigeria database (CBN), the National Bureau of Statistics and World Bank. The South African economic data comprised time series for a fifteen-year period between Quarter 1 (Q1), 2003 and Quarter 4 (Q4), 2018. The Nigerian data comprised time series for a ten-year period between Quarter 1 (Q1), 2008 and Quarter 4 (Q4), 2018. The logit model was proposed among others as a macroeconomic modelling approach that captures the future rental directions based on the general economic movements and likely turning points. The model is particularly useful due to its reliance on macroeconomic and indirect/listed real estate data which are more readily available to real estate investment decision-makers. This study identified that coincident indicators and the exchange rate both have positive significant relationships with Johannesburg Stock Exchange (JSE) listed real estate as compelling indicators for the South African market. For the Nigerian listed real estate market indicator, the model also responded to interest rate, the consumer price index and the Treasury Bill Rate (TBR) as reliable indicators. In addition to this, analysis revealed the logit regression framework as an improvement to naïve or ordinary linear rent models in these emerging African real estate markets. The use of macroeconomic modelling proved to be a viable alternative to scarce comparable transaction data which serve as the bedrock of traditional real estate investment appraisal. Thus, a forecasting model for early detection of turning points in commercial real estate rental values in South Africa and Nigeria was developed for use in real estate investment decisions. The study concluded that not all economic indicators lead the listed real estate market. The relationship between the

macroeconomy and listed real estate is largely significant, but this could be a positive or negative relationship.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1.

PREAMBLE AND BACKGROUND TO THE STUDY

1.0. Introduction

Forecasting rent behaviour is an important part of the investment decision-making process for local and foreign real estate investors. Investors view real estate as an asset class competing against other investment opportunities in stocks and shares. For this reason, understanding rent behaviour and the future trajectory of real estate movements provides a basis for decision-making. According to Munusamy, Muthuveerappan and Baba (2015), forecasting is critical in real estate because past transactions provide a basis for present and future decision making. They also suggest that forecasting the direction of movement in value is principally linked to the state of the economy occasioned by government policies. A few studies that have investigated the relationship between the economy and real estate forecasting exist in the developed economies (Krystalogianni, Matysiak and Tsolacos, 2004; Jadevicius, Sloan and Brown, 2013; Guerard, 2013).

The introductory chapter in this research is designed to provide details relative to rental forecast, setting the stage for a more rigorous debate towards the development of reliable models that are suitable for predicting rents in the Nigerian and South African real estate markets, accordingly, the remainder of the chapter is divided into seven sections including the following: Section 1.2 provides the background leading to the study. Section 1.3 states the research problem that prompted this study. Section 1.4 briefly outlines the research questions, while Section 1.4 deals with the research aim and objectives. Then follows Section 1.5, which contains the justification for this research. Section 1.6 dwells on the scope of the current research work. A brief research methodology is outlined in Section 1.7. Lastly, Section 1.8 sets out the structure of this research as it appears in all chapters.

1.1. Background

Real estate is one of the sectors that contribute to gross domestic products (GDP) of countries worldwide. Hongkong and Shanghai Banking Corporation (HSBC) (2017) reported that real estate assets were valued at $228 trillion in 2016 alone, while Gordon (2016) noted that global real estate accounted for 60% of mainstream global assets and about three times the size of global GDP in 2015. These figures show that real estate attracts a lot of investment and has even more potential to grow. The attractive nature of real estate stems from its undeniable features, including the ability to provide regular streams of capital or income, ease of conversion to cash, taxation advantages, durability and inflation-hedging characteristics. These features are what contribute to the sector's huge patronage by local and international investors and thus enhances a nation's investment climate.

The investment market is highly competitive and requires the real estate analyst to seek the best practices in information gathering. This informs the idea in this research that economic forecasts and rent movements can be better evaluated by modelling their relationship. This relationship becomes a significant part of global investment activities, because economic movements include effects from the real estate market and vice versa. Crosby and Henneberry (2010) support this with the argument that financial practices that involve calculations such as real estate investment appraisals are crucial to the makeup of the economy. In developing or emerging markets like Nigeria and South Africa, the lack of a central data pool or the scarcity of transactional data makes economic modelling even more important. Property analysts in developed economies have an easier task when forecasting rent behaviour from central data pools. The UK Investment Property Databank (IPD) has for instance over the years been used to undertake market forecasts, which is a source of information for investor decision-making in that country.

Growing interest in emerging African markets must be supported by improved accuracy in forecasting and reporting to stimulate investments. In Nigeria, the Residential Auction Company (RAC) Housing Price Index and the Roland Igbinoba Housing Price Index are attempts to employ transaction prices, averages and hedonic pricing models (HPM) for predictive modelling. Olowofeso, Bada and Dzaan (2008) noted the huge role that the nature of available data plays in the failure of these models or indices to provide much predictive information. Despite the wide acceptability of the HPM across international borders, it might not prove effective for predictive price movements in African markets. Abidoye and Albert (2018) investigated the accuracy of HPM as an econometric and advance valuation model. They concluded that about 60% of the predicted real estate values produced an inaccuracy that is ± 20% of the actual values. They also found that most valuations using this model had focused on explaining rather than predicting the market. It is important to investigate the relationship between macroeconomics, space and capital markets and predictive models in order to provide more accurate predictions.

In order to achieve this objective, various studies investigated the macro economy, monetary policies of the central bank and relationships with Nigeria's Real Estate Investment Trusts (Yunus, 2012; Olanrele and Said, 2014; Olanrele, Said and Daud, 2015; and Olanrele, Adegunle, Ayodele, Olaleye and Araloyin, 2016; Fateye and Ajayi, 2019). These studies attempted to evaluate the listed property, Real Estate Investment Trust (REIT) market in Nigeria and the influence of macroeconomic variables on performance. Olanrele, Said and Daud (2015) noted that Nigerian Real Estate Investment Trust (N-REIT) is a low- capitalised stock with no significant contribution to the market index. Considering the interest of investors to add real estate to their mixed portfolios, it is, however, important to understand the macroeconomic influences that drive growth. There is also a need to provide insight about emerging market trends to boost investors' confidence in the skills of the asset manager or real estate analyst. Property analysts in the African market who are unable to build this trust in their assessments might struggle to attract investors. In addition to this, the sustainability trends driving business in the real estate industry demand greater transparency about all aspects of doing business today (Potgieter, 2017).

In South Africa, Clark and Daniel, (2006) developed a suitable econometric model for forecasting South African house prices to address the issue of limited or scarcity of tools for real estate analysis in South Africa. Sibanda (2013); Emerole (2018); and Ntuli and Akinsomi (2017); Akinsomi, Mkhabela and Taderera (2018), all undertook studies relative to real estate and macroeconomic indicators. However, the recent study of Akinsomi *et al*. (2018), is worthy of attention, because it considers the macroeconomic drivers of direct real estate returns. This study built more on the existing literatures through a comprehensive analysis of market indices with techniques not previously used in the South African real estate market, and perform a relative comparison with another market within the sub-Saharan Africa.

Transparency is reflected in the availability of data-driven investment reporting and analysis with consideration for methods which can be accurately measured and goes beyond rule of thumb or the private judgement of analysts. Since the investment market is dominated by competing alternatives, accurate predictions of rents are needed to enable the investor to make informed decisions regarding the real estate sector. Olanrele *et al.* (2019) in a recent study focused on evaluating the causal relationship between N-REIT's dividend yield and money market indicators (MMI). They concluded that there was indeed a relationship between REIT returns and the MMI variables both in the short run (through Trace) and long run (using Max-Eigen values). This study limits its research to data from a single REIT which is the Skye REIT and does not provide much with regard to the future trajectory of prices and consequently the underlying real estate market. According to Emerole, (2018) in a study of

Nigeria and South Africa, as emerging markets get more liquid and transparent they will present better opportunities for investors. The study also suggests that investment will flow to emerging markets that represent lower uncertainty as regards transparency of market information. The accuracy in explaining rental behaviour and ascertaining its immediate future trajectory is an important theme in real estate market forecasting. Thus, the analysts sometimes obtain relevant information from own subjective observations, market indicators and predictive models to advise investors. For the avoidance of subjectivity, a greater premium is placed on the predictive models for early detection of turning points in rental values than on other information-gathering approaches. It is important to investigate macroeconomic models for their accuracy in forecasting.

This study argues that a lack of adequate growth and substantial returns in the real estate sector in Sub-Saharan Africa is a direct consequence of the lack of proper use of modern rental forecasting tools and clear identification of leading economic indicators and turning points. It thus seeks to investigate how much forecasting accuracy can be achieved by modelling the relationships between listed real estate and macroeconomic time series.

1.2. Problem statement

Inadequate information increases investment risk and uncertainty in investment decision-making. In emerging real estate markets such as in Nigeria and South Africa, investment analysts would seek to prioritise risk minimisation using improved forecasting approaches that capture signals from the economy. Iroham, Oluwunmi, Simon and Akerele (2014) suggest that comparable sales and historical data have primarily been used in traditional investment analysis and some advanced models like the HPM, with minimal accuracy in predicting rent patterns over time. They believe that the lack of a uniform benchmark for measuring rent behaviour is caused by the heterogeneous nature of real estate and overreliance on comparable transactions data. This kind of data may not be adequately available for capturing turning points in the real estate market.

Iroham *et al.* (2014) also observed a scenario in Akure, Nigeria, where the real estate market is characterised by frequent change in use from residential to commercial relative to location owing to the increased demand for commercial properties. Such information might serve an immediate purpose but is practically unreliable for predicting future rental movement. As is mentioned in Bello and Yacim, (2014), comparable data as the bedrock of most rental value assessment is sparsely available in most emerging markets. This makes it difficult, if not impossible, to rely on historical data for rent forecasts. Using listed property data, however, forms a good source of information that can be investigated with reference to the economic influences that affect the underlying assets. This drives the attention and focus on the extraction of market signals from economic data.

As discussed in Tsolacos, Brooks and Nneji (2014); Harrami and Paulsson (2017), the signals from macroeconomic leading indicators should be considered as great source of information on the movement of rental markets. Karakozova (2005), in a study of the Finnish real estate markets, also discovered that commercial rents in all nine cities behaved in broadly the same way. They held that the demand and supply drivers were mainly explained by national macroeconomic factors.

A lot of research has been done to promote macroeconomic modelling as a means to improve forecasting accuracy. Michael and Almeida (2016) discussed the investment market in the United States relative to predicting commercial market bubbles as a part of decision-making for global investors. They posited that in creating predictive models, identifying the “right” set of variables that combined to trigger changes in the market was a first step in predictive modelling. According to Oni (2010), the heterogeneous nature of real estate and the rapid change in Highest and Best Use (HBU) make it impossible to rely on direct real estate indicators for the sake of modelling future and current rent behaviour. The difficulty involved in translating some indicators into economic terms could make modelling produce inaccurate results.

According to Anderson and Cordell (1988) most of the benefits of tree shade are, for instance, difficult to translate into economic terms, yet some of them may be captured in the real estate values for land on which the trees stand. Alternatively, macroeconomic data and influences are largely numeric and quantifiable, a fact that gives them an edge over other drivers of demand and supply which could be useful for predictive modelling. The important differences between various properties include not only tree cover, but size, special features and location within the subdivision, among other factors. Appropriate comparable evidence of past sales/rentals is often difficult to obtain in determining the market value that trees can add when traditional valuation methodologies are used. For each of these speculative variables, the information provided eventually relied on the private opinion or judgement of the manager, appraiser or analyst. The level of uncertainty involved in such a process is too high for investors to make informed decisions.

Property is a part of every economy and it is important to understand its interaction with the economy. In modelling rent behaviour, investors are also much concerned with investible assets. This shifts the attention from residential to commercial real estate interaction with economic data, as most of residential real estate is not considered investible and the level of risk negligible. There are various types of uses of commercial space, such as industrial, office and retail space. All these segments of the real estate market affect or contribute to the economy in various ways.

A predictive and economic forecast could attempt to evaluate listed real estate data as a proxy for direct rent modelling. The commercial real estate sector is also of interest because of the data available in the form of listed real estate indices in the capital market. It is the view of Standish, Lowther, Morgan-Grenville and Quick (2005) that no freely available analysis of the residential real estate sector in South Africa exists. Existing models are owned by real estate valuation firms, agents and banks and are thus not in the public domain. The listed real estate data could provide data which is not privately owned and more likely to give an unbiased outlook for investible commercial real estate assets.

This implies that modelling starts to look away from unreliable rent determinants like tree shade and more towards a reliable mix of economic data which influence the commercial real estate market as an investible asset class. With the use of leading economic indicators we can model the relationship between macroeconomic movements that is lacking in the case of listed commercial real estate over the short or long term.

1.3. Main research question

What are the most reliable economic indicators for rental forecast in the Nigerian and South African real estate markets?

1.3.1. Research sub-questions

The core research question is subsequently divided into the following sub-questions:

1. What leading economic indicators exist for modelling and forecasting of commercial real estate rent?
2. How well do existing predictive models perform relative to identified economic indicators?

3. Can a relationship be established for early detection of turning points in commercial real estate rental values?
4. How well do the predictive models perform with leading economic data from South Africa, as compared to Nigeria?

1.4. Aim and objectives

The aim of this research is to develop predictive rent models for the Nigerian and South African real estate markets.

To achieve this aim, the following objectives were pursued:

1. To identify leading economic indicators for modelling and forecasting of commercial real estate rents;
2. To evaluate the performance of predictive models relative to the identified market indicators;
3. To develop forecasting models for early detection of turning points in commercial real estate rental values; and
4. To compare the relative performance of predictive models in identifying leading economic indicators in Nigeria and South Africa.

1.5. Justification of the study

To justify this study, it is important to explore real estate asset pricing globally and in Africa, most importantly in terms of how future or expected rent affect property value appraisal. Crosby and Henneberry (2010) propound that as a part of the economy and the wider business world, real estate is not immune from the changes affecting calculative practices more generally. This demand for improved predictive analysis may suggest a bigger structural transformation in the way value is measured in emerging economies like those of Nigeria and South Africa. The Royal Institute of Chartered Surveyors (RICS) and the

Investment Property Forum (IPF) had likewise held debates, set up committees and formulated responses, etc., to address the numerous concerns about suitability of valuation techniques in pricing. These included questions such as: If transactions were infrequent, then how can valuers claim that they used comparable methods? Can data from beyond direct real estate markets, like indirect real estates, provide relevant analysis? Is it possible to employ cash flow approaches for market valuations (Crosby and Henneberry, 2010)? The market is larger than single transactions and hence forecasts must be capable of handling big data which in this case refers to macroeconomic data and influences.

Tonelli and Cowley (2004) showed that an understanding of the past behaviour of the rent-component was valuable for evaluating future behaviour. Accordingly, Aron and Muellbauer (2009), used mortgage rates and other proxy indicators of rent, with caution because it might be misleading. In the Nigerian context, Ibiyemi and Adenipekun (2013) noted the deficiency in the use of cost, income and sales comparison approaches, which had affected investors' confidence. The fact that real estate is viewed as an asset class like stocks and equities is a major part of a transition to macroeconomic and financial investment analysis. It changes the possibilities with data and analysis for investment decision-making.

Boshoff (2013a) investigated listed real estate assets and brought together the two different asset classes, i.e. the stocks and bond market and the real estate market, as similar entities. The study asserted that price detection occurred in the listed real estate market, which could be a signal of market movement also in the direct real estate market. In order to make inferences about the market, analysts have to model the relationship between indirect real estate and macroeconomic data. Boshoff (2013a) also discovered that data from the indirect real estate market could serve for understanding the direct real estate market in South Africa.

The commercial real estate sector suffers from data limitations (Boshoff, 2013b). The information that shareholders can access from listed property companies to make investment decisions was investigated and it was found this kind of information, though scarce, can be useful for mass valuation purposes. A multiple regression analysis with empirical testing of property loan stock (PLS) companies in South Africa was employed. The emphasis was on the limitation for individual property valuation due to available information. The study suggested, however, that the possibility for statistical modelling based on listed real estate data is potentially great. There is also evidence that it is possible to extrapolate listed real estate information that is publicly available, in view of other properties for which the values are not known, using the properties' attributes to predict the individual value. Modelling the relationship between the real estate market and economic variables allows for forecasting and reporting. This potentially provides a reliable basis for investment decision-making in emerging markets like those in Nigeria and South Africa.

Udoekanem and Ighalo (2015) examined the drivers of office rent in Abuja, Nigeria. The research represents one of the few bold attempts to discover and model the relationship between commercial property markets and macroeconomic variables. Inasmuch as indirect real estate data might not replace direct real estate evaluations, they can serve as additional information for accounting and audits which provide insight to investors. Also notable is the fact that Probabilistic Predictive Models (PPMs) have proved to be effective in periods of low markets where scarce transactions limited comparative assessments. PPMs provide valuable indicators to evaluators about the likelihood an incline or decline of the market. This is important for emerging markets such as in South Africa and Nigeria, as was discussed and it is important for a lot of African economies, including South Africa, because contemporary methods of valuation have been employed in view of achieving better predictive capabilities.

Econometric modelling used in developed economies for investment and real estate forecasting points to a growing application to investment analysis. Thus, several studies were developed across more advanced economic contexts that support this paradigm. Harrami and Paulsson (2017) investigated rent modelling for the Swedish office market using economic theory and econometrics to model their investigation. Karakozova (2005) undertook a similar study in Finland to identify the drivers and the best methods for modelling and forecasting property rents and returns in evolving markets. They also employed econometric tools for their investigation. Tsolacos, Chris and Ogonna (2014) investigated the forecasting of future rent growth in the United States commercial real estate market using a Probit and a Markov-switching model. Moolman and Jordaan (2005) executed a similar study in South Africa which presents the relationship that exists between using leading indicator series and investigating turning points.

These and many other studies of econometric modelling and forecasting of rent markets justifies the investigation of the specific application of econometric modelling to pricing in the emerging markets such as Nigeria and South Africa. This dissertation is designed to identify leading economic indicators within the two countries and investigates their relationship with the listed real estate indices. The resultant model sought to contribute towards investment analysis by providing directional forecasts or appraisal of future rent trends in markets where transactional data are sparse.

This study fills a major gap by investigation of the use of econometric models for evaluating real estate rent as a part of the indirect or listed property and sought to provide a thorough discussion on the capacity of leading economic indicators to drive the real estate market and detect turning points. Not all indicators would have this capacity and it is important to understand the process of selecting the data and indices used for predictive rent modelling.

This insight helps the analyst understand the useful economic data for modelling rent behaviour. An early detection of turning points in the rent trends would also be useful for investors who would then be able to make informed buy or sell decisions in the market. This reduces the risk and uncertainty to a large extent and boosts investor confidence in the market. Major stakeholders in real estate investment will benefit from the results of this research. At the end of the study, investors and real estate analysts should have better insight into real estate forecast models within data limitations and using leading economic indicators.

1.6. Scope of the study

This study seeks to explore econometric modelling approaches useful for the development of predictive rent models in Nigeria and South Africa. Examples of models identified and assessed in this report are the Probit, Logit and Markov Switching (MS) models, which are a few nonparametric predictive models found to be useful for assessing turning points in time series data. Focusing on statistically relevant models would eliminate the risk of under-pricing or overpricing when carrying out assessment through traditional and conventional valuation methods.

As simple as it may seem to attempt an evaluation of the rent market, this is not so easy. The limited access to rental data in most cases limits reporting and decision-making. This research therefore pays attention to listed real estate data as sourced from the Iress Experts database. To proceed with modelling macroeconomic and real estate relationships, this report identified leading economic indicators that could give reliable signals for commercial real estate forecasts. This dissertation focuses on the commercial real estate market in Nigeria and South Africa, particularly the listed real estate indices which provide data consistent enough to make econometric inferences in relation to the general economy. The decision to focus on commercial listed real estate data is based on the weakness of data in the development of rent models using the residential real estate data.

Boshoff (2013c) and Keng (2004) suggest that listed data and economic time series are useful for evaluating the future trajectory of real estate markets which would help investors make better capital divestment decisions. This informs the choice of two locations in the sub-Saharan Africa for better decision marking. Additionally, the sizes of the two markets play a key role in the choice. Nigeria is Africa's most populated country, while the population of South Africa has been estimated at approximately one-third of Nigeria's population. In recent years Nigeria and South Africa have both been rated as Africa's largest economies, (Naidoo, 2019).

Rossouw (2016) also suggests that the two economies had experienced similar growth patterns enough to compare their performance. The two economies have experienced major shocks and economic prospects and are still fraught with uncertainties. Investors are likely to perceive these top economies in a similar light despite their population differences. Inflation, bubbles and economic recessions are shock effects which would also affect the real estate sector, as in the 2008 recession. Although residential and commercial real estates are investors' choices depending on motives, the commercial real estate is preferred in this study. Again, rents than prices is chosen, because rents denote the cash inflow that investors (landlords) of commercial real estate collect as their main source of returns.

1.7. Methodology

The approach for this research uses the turning point (TP) analysis based on the Logit Model. Time series data were collected from Stats SA and the Reserve Bank SA Database of all identified leading economic indicators for at least fifteen years. The historical data from Quarter 1 of 2003 till Quarter 4 of 2018 capture periods of major economic activity and recessionary trends that were observed in South Africa. The Nigerian Bureau of Statistics, CBN and Iress Data also report major economic shocks in Nigeria in this time lag during a period of ten years.

There are missing values in time series of each leading indicator selected from South African literature and a fifteen-year period could not be sufficiently covered, which limited the scope of investigation to a fifteen-year period while missing values were replaced with the closest available data. Once the consistency of data was established, the series were evaluated for their relationship with listed data time series. Economic indicators were regressed against a listed real estate index and testing of coefficients yielded a probabilistic predictive model showing the relationship between economic and real estate market movements.

SA indicators with time series that were consistent for fifteen years were accepted as reliable indicators and these were put through a correlation analysis to test for co-movement. The same was applied regarding Nigerian variables, but for ten years. This relationship between economic variables and the real estate index was intended to derive a predictive rent model. A Binary Logistic Regression (Logit) analysis with the Johannesburg Stock Exchange (JSE) listed real estate time series as the response variable was conducted. Also, a Binary Logistic Regression (Logit) analysis with the N-REIT listed real estate time series as the response variable was conducted. The Logit approach to modelling provides investors and analysts with an adequate basis for econometric modelling and directional forecast.

On the one hand this achieves improvement from the use of expert opinions and the judgement of analysts, while also overcoming the unavailability of direct real estate data. On the other hand, it simplifies the use of leading time series for forecasting rent patterns. This method also makes it possible to evaluate the predictive capacity of leading indicators and their ability to provide warning signals for shifts in the market.

1.8. Organisation of the report

- Chapter 1: This is the introduction to the research reports and provides a background to the research.
- Chapter 2: The literature review provides insight into related research and concepts. This was done chronologically according to publication dates to show how the concept of predictive modelling had evolved through research.
- Chapter 3: This describes the method by which data was captured and analysed. This also describes the models used in this research.
- Chapter 4: The discussions of findings and inferences were made in this section.
- Chapter 5: This is the conclusion and recommendations of this report.

In the next chapter, the second and third sections of the literature review indicate a growing body of research that pushes towards a more econometric approach to predictive rent modelling. These serve to mitigate risk and uncertainty in real estate investment by investigating models of real estate markets and the economic drivers which provide enough data insights as against a reliance on direct real estate data.

This approach hopefully addresses the problem of data unavailability. It also helps the real estate analyst to take a more explicit approach to evaluating economic influences on real estate performance. The rising demand for transparency in real estate investment is an opportunity to understand the available data and indices for real estate market analysis in emerging Africa. This research attempted to provide an answer to the problems of risk and uncertainty which undermine investment in African real estate markets by developing a predictive rent model for the Nigeria and South African markets using a Logistic regression approach.

In the next section, various studies and the research that has been conducted in line with similar objectives to those in this study are examined.

CHAPTER 2.

LITERATURE REVIEW

2.0. Introduction

This chapter focuses on the review of relevant literature with regard to modelling the relationship between leading macroeconomic indicators and indirect real estate in emerging markets. Literature on identifying and understanding the leading nature of macroeconomic indicators serves as a basis for modelling commercial property rent trends and early detection of turning points. The review seeks to assess the existing body of knowledge to evaluate and improve the modelling process for African real estate markets such as those in South Africa and Nigeria. This research examines existing literature and the growing study focus which continues to expand the frontiers of investment analysis across various markets.

The intention of this study was to explore the process of modelling macroeconomic influences on the forecasting of rent while seeking to improve on existing flaws in some of the traditional valuation and real estate pricing methods. The literature surrounding the identification of leading indicators in a predictive rent model was also examined.

The review was undertaken thematically to capture the various sources of literature identified within the scope of the research objectives which included to:

1. Identify leading economic indicators for modelling and forecasting of commercial real estate rents;
2. Evaluate the performance of predictive models relative to the identified market indicators;
3. Develop forecasting models for early detection of turning points in commercial real estate rental values; and

4. Compare the relative performance of predictive models in identifying leading economic indicators in Nigeria and South Africa.

The gap in the literature that was identified by means of this review informed the data and the method of analysis employed in the subsequent fourth and fifth chapters.

In accordance with the above, the chapter comprises six sections: Section 2.2 reviews the studies related to leading indicators for forecasting commercial real estate rental values. Section 2.3 discusses real estate as an asset class influenced by macroeconomic leading indicators. Section 2.4 focuses on modelling the relationship between leading economic indicators and the real estate market. Section 2.5 discusses modelling turning point signals and, lastly, Section 2.6 provides the summary and conclusion of the chapter.

2.1. Leading economic indicators for modelling and forecasting of commercial real estate rents

According to Abidoye and Chan (2016), the valuation of real estate is an estimation of the value at which real estate will exchange in the open market. In the context of investment valuation, the ability to estimate how much a property will exchange in the market relies on an estimate of the present-day value of future rental income over the life cycle of the property. In other words, the capital value of property today, reflects the estimated future values of rent receivable from the property. The role of rental or predicted rental values thus becomes a crucial part of investment valuation and analysis. It is important for analysts to be able to estimate the future trajectory of rent and rental figures for evaluating investment value today.

According to Tsolacos and Brooks (2010), real estate data can be generated through the valuation process. Rental forecasting provides information that's critical for the valuation process. However, the infrequent nature of real estate transaction data makes it important that real estate valuation should take place by using the drivers or influencers of value. The econometric study of relationships in real estate and the forecasting process draw upon the general subjects of econometrics and economic forecasting (Tsolacos and Brooks, 2010).

Hence, studies have been devoted to understanding these econometric interactions. Identifying leading indicators is a significant part of the forecasting process. Macroeconomic variables play a significant role in understanding the growth and performance of real estate. According to Özyurt (2014), commercial real estate markets in the Netherlands interact significantly with macroeconomic activity and the financial systems. Modelling these interactions require analysts to select from several possible economic variables that interact significantly with real estate and rent movements. Inherently, if the indicator signals and data are not valid, the model that is constructed, would only give spurious values.

Table 2.2 shows a list of prospective leading indicators in the South African economy as compiled by Moolman & Jordaan (2005). This indicates a history of studies surrounding the understanding of the leading roles of economic variables and the forecasting process.

Table 2.1 South Africa prospective leading indicators (Moolman & Jordaan, 2005)

Series	Description	Transformation used[6]
	Interest rates	
RS	Short-term nominal interest rate	
RL	Long-term nominal interest rate	
SPR	Yield spread, defined as the difference between the long- and short-term interest rates	
	Monetary aggregates	
M3	Nominal M3 money supply	Year on year growth
M2	Nominal M2 money supply	Year on year growth
M1	Nominal M1 money supply	Year on year growth
CL	Construction loans	Year on year growth
	International indicators	
NEE	Nominal effective exchange rate	Year on year growth
R$	Rand-US$ exchange rate	Year on year growth
TR	Composite index of leading indicators of trading partners	Year on year growth
	Macroeconomic indicators	
BP	Building plans passed	Year on year growth
NO	Manufacturing, new orders	Year on year growth
CIL1	Composite Index of Leading Indicators	Year on year growth
CIL2	Composite Index of Leading Indicators	Percentage change
SB1	SACOB Business Confidence Index	Level
SB2	SACOB Business Confidence Index	Percentage change

In modelling rent behaviour, interactions from the demand side of the commercial property market are commonly represented with economic indicators like the Gross Domestic Product (GDP) and employment. It is important to identify which indicators are significant drivers. Baba & Kisinbay (2011) propose a data-based algorithm to select a subset of indicators from a large data set with a focus on forecasting recessions.

Ng and Higgins (2007) focus their study on understanding the key determinants driving commercial real estate market performance. They suggest that the GDP, the unemployment rate and office Finance, Insurance and Real Estate Services (FIRE) employment are the key determinants on the demand side of the rent determination. Namnso, Ighalo and Sanusi (2015) conducted a study of office rent drivers across three districts in Abuja, Nigeria. They found that real GDP growth and the vacancy rate were the major determinants of rental growth. MacFarlane, Murray, Parker and Peng, (2001) identified employment as the main driver of demand for office space. D'Arcy, McGough and Tsolacos (1999) also reported that two economic variables were used to capture the demand for office space, Gross Domestic Product (GDP) and Service Sector Employment (SSE).

Two macroeconomic indicators stand out in literature. These are:

1. The Gross Domestic Product (GDP); and
2. Employment.

Boshoff (2013) reports that growth in real per capita consumption, real short-term interest rates, the real-term structure of interest rates and unexpected inflation were found to be fundamental drivers that systematically affected returns of both direct and indirect real estate markets in the United States. Clark and Daniel (2006) also list eleven economic and financial variables to be considered for inclusion in the regression model for forecasting South African house prices.

These variables are:

1. The All Share Index.
2. The prime rate of interest.
3. The Gross Domestic Product.
4. Building plans.
5. Business confidence.
6. Motor vehicle sales.
7. Household debt/disposable income.
8. The rand/dollar exchange rate.
9. The real gold price.
10. The real oil price.
11. Transfer costs.

Table 2.2 likewise indicates the significance of indicators considered by Frankel and Saravelos (2012) for detecting early warning signals.

Table 2.2 Statistical significance of indicators for crisis signal (Frankel and Saravelos, 2012).

Leading indicator[1]	KLR (1998)[2]	Hawkins and Klau (2000)[3]	Abiad (2003)[4,6]	Others[5,6]	Total
Reserves[a]	14	18	13	5	50
Real exchange rate[b]	12	22	11	3	48
GDP[c]	6	15	1	3	25
Credit[d]	5	8	6	3	22
Current account[e]	4	10	6	2	22
Money supply[f]	2	16	1	0	19
Exports or imports[1a, g]	2	9	4	2	17
Inflation	5	7	1	2	15
Equity returns	1	8	3	1	13
Real interest rate[h]	2	8	2	1	13
Debt composition[1b, i]	4	4	2	0	10
Budget balance	3	5	1	0	9
Terms of trade	2	6	1	0	9
Contagion[j]	1	5	0	0	6
Political/legal	3	2	1	0	6
Capital flows[1c, k]	3	0	0	0	3
External debt[l]	0	1	1	1	3
Number of studies	28	28	20	7	83

This research is established on the notion that valuation accuracy and forecasts in real estate can be improved using econometric modelling of leading indicators. In Tsolacos and Brooks (2010), real estate data are compared to economic data and a similarity is established in terms of their frequency, accuracy, seasonality and other properties. A variety of literature on real estate forecasting and modelling has focused the attention on the relationship between economic, real estate and financial data. Some popular works in these subject areas include studies such as those of (Tsolacos (2012); Jadevicius, Sloan and Brown (2013); and Boshoff (2013a); Munusamy, Muthuveerappan and Baba (2015); Olanrele *et al.* (2019)) evaluated the relationship between five Money Market Indicators (MMIs) which comprise: Currency in Circulation (CIC), Broad Money Supply (BMS), the Corporate-Private Sector (CPS), the Prime Lending Rate (PLR), the Treasury Bill Rate (TBR) and the Nigerian Real Estate Investment Trusts (N-REITs). They conclude that PLR, CPS and TBR demonstrate a significant outcome on REIT yields which are all in different directions.

This dissertation seeks to model leading macroeconomic data while improving real estate forecasting and accuracy. The significance and performance of these indicators in modelling rent behaviour requires further investigation into the causal relationships and accuracy of such models in forecasting rent.

2.2. Leading indicator Series

To resolve the data problems and scarcity of transaction data, alternative data sources were examined for their capacity to provide reasonable insight into the market trends. The analyst must decide on relevant data sources for the variables to be used in the modelling of economic trends. This also makes it possible to understand the nature of data that must be gathered in the emerging markets. Data sources for modelling are important, because they determine the validity of the outputs from models. The nature of data available also determines the appropriateness of the model. They determine the capacity of models to predict turning points for the property markets where transaction data is hard to come by. This could significantly improve modelling accuracy in emerging markets as in South Africa and Nigeria.

Frankel and Saravelos (2012) carried out their investigation on leading indicators using data and variables extracted from the World Bank World Development Indicators database, monthly real effective and nominal exchange rate data from the IMF International Financial Statistics database, which presented a collection of about fifty economic indicators dated as far back as 2007. It was noted that the availability of these data sets differed from country to country. This study also grouped the variables into those that were dependent and those that were independent.

The categorisation included:

1. Independent variables, which were labelled in groups such as reserves, Gross Domestic Product, credit, current account, money supply, inflation, equity returns,

interest rate, debt composition, legal/business variables, capital flows, external debt, regional/income dummy variables.

2. Dependent variables, which were major crisis indicators such as GDP change, industrial production change, change in local currency vs. USD, annualised returns/standard deviation of benchmark stock index.

The study did not subject its investigation to changes in property-related dependent variables. This indicates an opportunity for further research using a rent- or property-related index as dependent variable in a predictive model.

According to the research report by Camacho and Perez-quiros (2000), the ability of the Composite Leading Indicator (CLI) to predict turning points depended on the model used and its ability to extract the signals or leading information from the data series. Their study recommended a combination of vector auto-regression and nonparametric systems to convert CLI leading indicators into probabilities of growth. They considered previous evaluations of the CLI and offered a filter that sought to unify the various approaches for detecting turning points and recession probabilities. The research was carried out using indicators within the United States real estate market. The Conference Board Leading Economic Index, Organisation for Economic Co-operation and Development (OECD) Leading Economic Indicator and other sentiment indicators were compared for their predictive abilities, using the two models.

Relevant data sources are a major consideration in forecasting. In Jadevicius, Sloan and Brown (2013), the Investment Property Data (IPD) all property value growth index for the United Kingdom was used for independent variables. Despite the availability of other data sources, this index was considered as reliable, based on usage and acceptability within the investment and property research community. They also worked with a list of potential lead indicators and reduced this list, using information from previous literature and stepwise regression. They argued that there was a need for at least fifty sample observations to produce an adequate time-series model. Forty-eight data points from the Investment Property Data (IPD) and Scott's datasets where reduced to eight explanatory variables and applied over a period from 1963 to 2010. The in-sample forecasting estimated that a ten-year period ex-post forecasting would be enough to test the performance of models and variables. This would contain two short periods of four to five years representing the typical business cycle, while the longer property cycle of nine to ten years would also be represented.

A lot of the research regarding investment and forecasting in Nigeria relied mostly on limited surveys and questionnaires. Examples included Iroham (2014) and Ibiyemi and Adenipekun (2013). Explanatory forecasting for examples requires, however, that analysts rely on historical data to explain future forecasts. This limits the usefulness of surveys that hardly exceed one to five years. Ibiyemi and Adenipekun (2013) recommended that data banks for property indices, accuracy tests and performance measurement like the United Kingdom IPD should either be set up by the Nigerian Institution of Estate Surveyors and Valuers (NIESV) or should be private-sector driven. Jadevicius *et al.* (2013) held that complex and more realistic models usually require greater amounts of data.

In Standish *et al.* (2005) the dependent variable, which was the average house prices, was provided by ABSA on a quarterly basis from 1974 to 2003. Other variables like nominal and real exchange rates, tourism and foreign direct investment were obtained from the JSE Securities Exchange. Anas and Laurent (2004) used the Eurostat data for the period starting in 1995 to detect cyclical turning points in the United States. Aron and Muellbauer (2009) also noted, while exploring issues in modelling and forecasting inflation in South Africa, that Stats SA had no data on rents before 1997. They concluded that this was too short a period for robust modelling. Economic data for these long periods can, however, be found. In order to improve on models, it would be required to identify other real estate demand and supply side indicator time series.

Clark and Daniel (2006) attempted to develop an econometric model for forecasting South African house prices for 2005/6. They noted that conflicting results were produced in identifying the relationship between real estate returns and stock market returns because some studies used physical (direct) property market data while others use securitised (indirect) property data. To avoid this conflict, this research focused on indirect property and on economic and financial data sources in South Africa and Nigeria. A lot of the data were accessible through sources such as the Stat SA database, the Nigerian Bureau of Statistics, the World Bank database and the Iress Expert Dashboard. These economic and financial data sources needed to be explored for their usefulness in rent forecasting.

2.3. Real estate as an asset class influenced by macroeconomic leading indicators

Real estate as an asset class reflects a relationship between financial and economic data. This relationship implies that leading nature of economic variables could serve as useful source of signals for impending shifts or turning points in the real estate market. This relationship between rent and the capital market is described by what is being introduced as the Space and Capital Market theory, (Boshoff, 2013a). Investment analysis has a long history of reliance on private judgements of experts in determining the movement and performance of rent and the overall course of the real estate market. French (2005), reported an increasing diversity in the property investment market undermines valuation techniques that rely heavily on comparison between relatively homogeneous investment assets and simple adjustments to comparable evidence.

A major limitation of judgement-based investment analysis is that investors might find that the available data do not provide much information about the rationale for estimates made, which makes it impossible for decision-makers to participate fully in the investigation of pricing and rental growth trends. In order to overcome this obstacle and to stimulate investment and finance decisions, there was a need for improved methods of modelling rent patterns.

This necessitated investigation of econometric models and the influence of variables which are more easily quantified and recorded in financial statements, business reports and similar sources that investors regularly rely on for decision making. Investigating the process of real estate econometric modelling and the leading economic indicators offers greater potential for identifying market signals. These leading signals could possibly be applied in a turning point analysis for identifying warnings of a changes or growth in rental values. According to Chrostek and Kopczewska (2013), economic models are hypothetical concepts used to characterise economic patterns. In the context of real estate and the real estate market, we can say that econometric models are theoretical constructs used to represent real estate related economic phenomena and their interaction with businesses.

Previous studies such as those undertaken by Burns and Wesley (1946) highlighted the need to establish the existence of a real estate cycle led by economic and business cycles. This research direction points to a need for econometric modelling and forecasting as a measure for detecting turning points based on selected leading indicator series. Econometric modelling approaches have been recommended from studies reported within markets like the United Kingdom and the United States, as seen in Füss, Stein and Zietz (2012); Tsolacos (2006) and Frankel and Saravelos (2012). This review identifies a need to develop a similar framework within the largest economies on the African continent as a replicable methodology for real estate market forecasts in a similar context where transaction data is limited.

Brooks and Tsolacos (2000) justify the applicability of predictive probability models for forecasting, based on signals from leading indicators. Likewise, Boshoff and Binge (2019) focus on the use of non-parametric turning point analysis, while identifying leading indicators in the South African business cycle. They hold that the requirement for selecting indicators should include co-movement with the general business cycle or economic growth indicators such as the GDP, and these should be stable. They have, however, failed to investigate the performance of leading indicators as part of econometric modelling and forecasting of rent behaviour in markets where transaction data is limited or unavailable.

In a technical report by Mourouzi-Sivitanidou (2011) the leading nature of the property cycle in reference to the business cycle is depicted as represented in **Figure 2.1**. The business cycle shows alternating peaks and troughs which identify the points of change in the market direction.

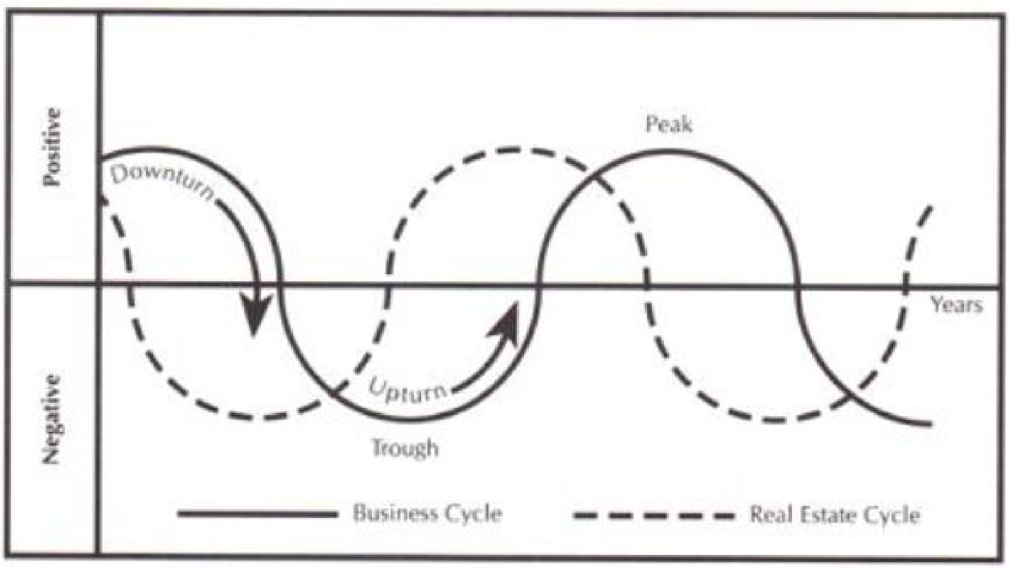

Figure 2.1 Business cycle and real estate cycle interaction (Mourouzi-Sivitanidou, 2011).

Leading indicators signal the fluctuations in markets which manifest as expansions or contractions. The leading indicator method is applied for predicting business variations and is entrenched in the understanding that there are repetitive patterns of growth and reduced economic activity (Krystalogianni, Matysiak and Tsolacos, 2004). In this approach, analysts identify economic indicators that reach a peak or a trough earlier than the macroeconomy peaks or troughs. The strategy employed is to identify these occurrences, dating them and forecasting the emerging stages. This practically implies early-stage detection of recessionary or recovery trends.

The importance of this approach for real estate forecasting is rooted in the leading nature of the economy relative to business or real estate cycles. According to Boshoff and Binge (2019), business confidence indicators possess analytical signals for economic growth and are frequently accurate leading indicators of turning points. In the United Kingdom and similar markets, information from leading indicators series have been confirmed to be useful for detecting early warning signals for economic turning points. As seen in Krystalogianni, Matysiak and Tsolacos (2004), leading macroeconomic variables in the United Kingdom market prove to be important for forecasting the recurring pattern of commercial real estate activity.

Boshoff (2013) opines that the information provided by indirect real estate investment, shows that analysts can rely on these data for evaluating the underlying assets or direct property market. The indirect real estate market also interacts with data that can easily be quantified and tested. The need to investigate further is also supported by the fact that indirect real estate analysis shows evidence of relationships with economic variables which can easily be quantified. Real estate at this level is considered to be like any other asset class and could be influenced by various economic and financial drivers. Valuation is then no longer just a point estimate but it encapsulates the relationship between the macroeconomy, direct real estate and indirect real estate investments.

The econometric modelling of real estate prices is an important step in their valuation (Chrostek and Kopczewska, 2013). To understand market trends, there is a need to understand the relationship of the overall economy has with the pricing of real estate assets.

2.4. Modelling the relationship between leading economic indicators and the real estate market

Being a major destination for real estate investment, there's growing focus on the African real estate market when it comes to modelling of leading indicator signals (Moolman and Jordaan, 2005). The lack of data implies that investors necessarily seek improved approaches for detecting and modelling the signals that can be extracted from macroeconomic indicators in the African market. Property investors and analysts require formal assessments of real estate forecasts given the practices elsewhere and the need for informed advice. Assessing the accuracy and information content of real estate forecasts are key ingredients for achieving credible forecasts and for model adjustments (Tsolacos, 2006).

This study seeks to replicate the most acceptable forecasting models within the largest African markets and thereby to develop an appropriate framework for modelling leading indicators in African real estate markets. Modelling local markets and the input of expert opinions have in time past served as basis for advising on investment decisions in local real estate markets. The heterogeneity of property makes it difficult, however, to capture all the individual sentiments and influences that could affect the prices of rent in local markets. In other words, to understand real estate market trends relative to the overall economy, analysts must look towards globally accepted indicators for signals of turning points and price changes.

Barnard and Oranje (2014) in their research focused on identifying proxy indicators for estimating performance of local South African economies. Inasmuch as this approach seemed to provide insight into economic activities, the limitations are too many, in that it does not work with enough data to give a full picture of the economy. Conclusions about the economy cannot be reasonably drawn from such a small sample. The study tested selected indicators in three sampled towns. This restricts modelling to rely on data only applicable to local markets and which cannot provide sufficient lag or lead periods for forecasting market movements.

These researchers also attempted to show a strong relationship between real estate indicators and local or regional markets. Such a test for correlation between local economic data and real estate markets provides very little information on the overall economic outlook and introduces bias across localities and regions. It also poses the challenge of gathering significant data that could serve for consistent and valuable inferences about market turning points and phases of expansion or contraction. This obvious limitation of local economic models necessitates further research into the business cycle as well as macroeconomic data which could provide investors with the needed insight for better decision-making.

Olawande, Emoh and Ijasan (2012) examine the relationship between money supply in the Nigerian economy and some money market indicators to discover their relationship with finance for real estate development in Nigeria. They discovered the existence of statistically significant relationships between money supply and macroeconomic drivers such as inflation, monetary policy rate, saving deposit rate, and treasury bill rate. They recommended Real Estate Investment Trust (REIT) as an ideal financier for commercial real estate in Nigeria. This study points to the increasing demand for REITs. However, they do not provide insight into the effect of these macroeconomic drivers on the commercial real estate sector which leaves room for this study to model such relationship if it exists.

Other studies that discuss the forecasting of commercial real estate in the Nigerian market such as Emele, Umeh and Okpaleke, (2019); and Udobi, Kalu and Elekwachi, (2016) have only managed to identify challenges to commercial real estate investment and forecasting in Nigeria but have not provided modelling approaches for addressing the risk and uncertainty inherent in attempts to invest in emerging markets like that of Nigeria and South Africa.

Barnard and Oranje (2014) noted that "even though the local economy might influence the number of residential building plans submitted, it is difficult to extract the data from the local municipality, and the data is often not recorded in a useful time-series format in municipal offices." Their study makes a commendable effort to create a simplified approach for resolving the data problem in forecast and predictions, but also concludes that these proxy indicators have poor predictive reliability. They seem to provide a simplistic approach for making better judgement assessments of the local economy. This may not be useful, however, for large-scale forecasting, neither would it serve the purpose of providing early warning signals for real estate investors.

2.5. Model performance in identifying leading economic indicators

Munusamy, Muthuveerappan and Baba (2015) considered a variety of literature regarding modelling types, accuracy and adoption of statistical modelling techniques. They reported that Multiple Regression Analysis (MRA) and Artificial Neural Networks (ANN) were most widely used. They concluded that ANN showed an average error rate between 5 to 10% inaccurate, while multiple regression analysis showed a higher average which was 10 to 15%.

Chrostek & Kopczewska (2013) compared the quality of prediction for several models: a classical linear model estimated with Ordinary least squares (OLS), a linear OLS model including geographical coordinates, a spatial expansion model, spatial lag and spatial error models as well as geographically weighted regression. They concluded that models comprising the spatial components rendered better estimates than a-spatial models. They added, however, that in order to improve the model, it would not be enough to apply only a simple method of adding coordinates' variables to the OLS model, as these new variables might lead to the overtraining of the model. There is evidence of the capacity of complex models such as these to predict rent behaviour.

There were, however, other researchers like Moolman and Jordaan (2005); Tsolacos (2006); Boshoff (2013); and Udoekanem, Ighalo and Sanusi, (2015) who preferred simpler models such as the simple regression, vector auto regression and binomial logit regressions. The volatility of simulations and training of models could introduce errors due to aspects of the model that cannot be explained a priori. The explanation of complex models and what constitutes a complex model can be seen in Jadevicius, Sloan and Brown (2013).

Udoekanem and Ighalo (2015) employ the single-equation regression analysis office property rents in the commercial property market of the Asokoro, Maitama and Utako districts. The developed office rent model accounted for 76%, 72% and 75% of the variation in office property rents across the three districts, further proving the almost equal capacity of simple models. Boshoff (2013), however, favoured the applicability of econometric models in the forecasting of property-market behaviour in South Africa. Tsolacos (2006) also supported econometric modelling as against consensus forecasting based on expert judgement in their study of United Kingdom property performance forecasts. They recommended the regression model and a combination with consensus forecasts for the two-year horizon. They also suggested a simple linear regression for the one-year forecast horizon.

The argument of Jadevicius, Sloan and Brown (2013); for simplicity presents an important position on model performance. According to the researchers, simple models outperform the more complex structures. They emphasise the need to simplify complex models and improve on simple models to make modelling more user-friendly. They also argue that combination forecasts are the best for improved modelling purposes. They mention econometric models as examples of complex models and linear regressions as examples of simple models. This study proceeds to investigate the ability of the logistic regression modelling to improve on the accuracy in rent forecasting.

In another study, Moolman and Jordaan (2005) used the Logit model to test whether leading indicators could predict turning points in the commercial share price index. The study concludes that in South Africa, this method of forecasting was receiving increasing attention. In their opinion, leading indicators, having longer lead times, could serve as indicators of turning points for share prices which had been found to lead the business cycle. Their study identified eight indicators, including building plans, which predicted the direction of share price up to 86% of the time tested. Despite the fact that rent growth or real estate value data were not explicitly examined, this research pointed to the capacity of construction and real estate indicators to serve as lead indicators.

2.6. Forecasting and early detection of turning points in real estate rental values

There is an abundance of literature about turning point analysis outside the South Africa and Nigerian context. In South Africa substantial effort has been made to understand the influence of cycles and turning points on forecasting and modelling of the macroeconomy and real estate. A few of these studies include; W. H. Boshoff and Binge, (2019); Aron and Muellbauer, (2009); Anas and Laurent, (2003); and Monde, (2008). These studies however focus mostly on how cyclical turning points can be used to forecast inflation. The dirth of literature on this subject as it applies to the real estate cycle in both South Africa and Nigeria is opens up opportunity to discover how turning points in real estate cycles are modelled in relations with the macroeconomy.

To understand the expansion and contraction phases, researchers work with various rule sets. There is a robust debate among researchers whether the focus should be on parametric or non-parametric models. Popular among these is Boshoff (2005). Their argument against the use of parametric models such as the Markov Switching is predicated on the lack of transparent rules as compared to the calculus rules seen with nonparametric models.

The need for a statistical basis for describing turning points also supports an argument for non-parametric approaches such as the Probit or Logit models. This is to avoid, among many other things, identifying circumstantial shifts in real economic activity. Boshoff (2005) presents a set of pre-determined rules that can be reproduced in the identification of turning points with corresponding business cycle peaks and troughs.

The censoring rules are as follows:

1. Turns within four months of the beginning/end of the series are eliminated.
2. Peaks or troughs lying next to endpoints and higher or lower than such endpoints are ignored.
3. Complete cycles with a total duration shorter than fifteen months are eliminated.
4. Phases shorter than six months are eliminated, except for excessive falls/rises (defined quantitatively in the empirical part of the paper) where a minimum phase length of four months applies.

Boshoff (2005) already provided a more detailed description of the turning point formula and analysis. More important to note is the applicability to South African data time series pulled from the real economy and other composite leading indicator series. The study also suggested that the observation of co-movements between leading indicators and the dependent variable was required to establish preliminary relationships.

2.7. Modelling turning point signals

According to Tsolacos and Brooks (2010) the aim of a turning point forecast is to identify turning points or the possibility of a turning point. Turning points analysis in the assessment of leading indicators of the economic time series provides an opportunity to predict the probability of a change in business cycle movements or direction. Monde (2008) defines turning point dates as those that differentiate between periods when collective economic activity improved at a rate stronger than or equal to its long-term growth movement (upward phases) and stages when collective economic movement either declined or reduced at a rate below its long-term growth trend (downward phases). In other words, a contraction or expansion point at which direction of growth changes significantly, can be defined as the turning point of that cycle.

Models that can accurately forecast the signs of future returns, or can predict turning points in a series, have been found to be more profitable (Tsolacos and Brooks, 2010). They recognise the significance of evaluating a turning point as prerequisite to developing warning signals from reliable leading indicators. If we cannot assess turning points in the real estate growth trend, then it is practically impossible to evaluate which indicators of economic growth can lead the real estate market and help real estate analysts make better informed decisions.

Tsolacos and Brooks (2010) held that research on early signals would and should focus on leading indicators. Leading indicators are used to capture changes in direction and turning points. The forecasting models are thus aimed at directional and probabilistic analysis. The researchers identified the Logit and Probit approaches as examples of turning point analysis where the dependent variable is always a figure between 0 and 1. How do we measure turning points? Monde (2008) clarifies this in saying that the first mark of an imminent turning point in the business cycle is typically when the composite leading business cycle indicator plainly changes course for a period of at least six months.

In their study, Krystalogianni, Matysiak and Tsolacos (2004) defined turning points as the change in direction when a swing in business cycle ends. Developing a composite leading indicator series is a crucial step in econometric modelling and forecasting in the commercial real estate sector.

2.8. The Chapter summary

The literature review thematically shows the growth of real estate investment analysis using macroeconomic leading indicators. This section explored the existing literature on the selection and sources of leading indicator data. It proceeded to investigate opinions about the influence of leading macroeconomic indicators on real estate as an asset class. The wide acceptability of econometric models for predicting turning points in the United Kingdom, the United States and other First World nations suggests that African markets might benefit from similar modelling techniques.

The operations of commercial or listed real estate were identified as a reliable source of market signals relative to direct or transactional data. The literature reviewed helped clarify the role of leading economic indicators in investment analysis. As a subject under real estate valuation, investment analysis provides a basis for capital allocation decisions, risk assessment and portfolio management. The evolution of valuation and econometric modelling are part of need for data-based approaches to decision-making. In this literature review, the relationship between economic, business and real estate cycles was discussed. It also considered the rules and basis for identifying leading macroeconomic indicators. In the reviewed literature, the focus for investment analysis shifted to the relationship between macroeconomic data and indirect real estate data. It is important for the analyst or real estate investor to understand the available data from which predictions can be made. In order for predictive rent modelling to perform adequately, data sources must be proved to demonstrate a relationship with identified economic data.

The use of leading indicator series for modelling in markets like the United Kingdom or United States shows the potential for similar modelling approaches in Nigeria and South Africa. The studies point to a use of Logit regression as a form of directional forecast. Considering the various positions on appropriate modelling technique, the binary logistic regression proves to be popular and devoid of complex parameters. This makes it desirable for further testing with African data sources.

In the next chapter, the economic data and sources identified from the literature review are regressed with the binomial real estate indicator. The performance of the outcome model determines the extent to which macroeconomic data can serve to improve the accuracy of predictive rent models. The literature reviewed, identified the econometric models and how listed real estate data are relevant to modelling rent trends. To add to the growing attention paid to quantitative analysis of indirect real estate data, this study proceeds with a focus on the relationships between macroeconomic data and commercial real estate data. It moves in the direction towards discovery whether a binomial logistic regression would truly provide a simpler model capable of reliable directional forecast, using macroeconomic data.

CHAPTER 3.

MODELLING TECHNIQUES

3.0. Introduction

This chapter explains the techniques used in identifying reliable variables and prediction of rents in this study and this serves to provide an overview of the underlying philosophies behind each of the modelling tools. The chapter also describes concepts leading to the use of these techniques in real estate analysis.

The chapter is divided into seven sections. Section 3.1 describes the rent model in relation to the demand and supply of real estate. Section 3.2 focuses on the evolution of statistical approaches and their usefulness in identifying leading indicators. Section 3.3 explains the concept of turning point analysis relative to real estate pricing. Section 3.4 compares various modelling approaches that are useful for detecting turning points and Section 3.5 describes the Logit and Probit regression models. 3.6. Explores the application of Probit and Logit regression for real estate forecasting. 3.7. Provides a chapter summary.

3.1. Rent modelling

Udoekanem, Ighalo and Sanusi (2015) describe the underlying concept of the commercial real estate market and thus the underlying concept for modelling commercial property rent as applied in Nigeria. Rental value is a function of demand and supply factors. That is:

$$R = f\,(D+S) + e \qquad \textbf{Equation 3.1}$$

R = commercial property rent

D = demand factors

S = Supply factors

e = Error term

Tsolacos, Brooks and Nneji, (2014), examine the relationship that rent values and series have with economic and market trends. They discover that this relationship has direct implications to prevailing beliefs about the forthcoming path in rents, because leading series are considered a gauge of the economy's future direction and strength. Their study explains that the leading indicator approach is based on the theory that there are cycles that indicate a repetition of expansion and contraction in economic activity like the business cycle. Leading economic indicators are sequences that are highest before the macro-economy and they reach a trough ahead of the macro-economy transitioning into an expansionary stage. Anas and Laurent (2003) also describe the modelling and detection of turning points as identifying these occurrences of expansion or contraction, dating them and forecasting the emerging stages. In practice, this translates into classifying the early phases of a downturn or a recovery. A great deal of investigation of business cycles focuses on the contribution of leading indicators in modelling and forecasting turning points in the economy as seen in Artis, Bladen-Hovell, Osborn, Smith and Zhang, (1995).

The OECD, the European Commission, the US Conference Board, private companies and other organisations evaluated certain series and built composite leading indicators to forecast turning points in the business cycle. Given the close association between the economy and the listed commercial real estate market, and if leading indicator series can effectively predict movements in the economy, these may serve as early indicators for future commercial real estate performance.

Similar models that show the rent space and capital market association in the South African market, display a growing interest in modelling rent activity. Tsolacos, Chris and Ogonna (2014), Tsolacos, Brooks and Nneji (2014) state that rents represent the cashflow that real estate owners receive. This implies that predictions of the future movements of rent may enable investors to better plan their real estate purchases or divestments.

Boshoff (2013a) focused on two real estate forecasting models within the South African market, which are the Real Estate Econometric Forecast Model (REEFM) and Fischer-DiPasquale-Wheaton (FDW) models. The study criticised the FDW model for its lack of econometric validity. According to Boshoff (2013a) the REEFM model improves the investigation into listed real estate markets by introducing the econometric side to the linear regression. This describes the space and asset markets' interactions with the overall economic performance. The conceptual framework for the REEFM model is illustrated in **Error! Reference source not found.**. This model illustrates the demand and supply drivers that influence the interactions between the space and capital market. The REEFM takes into consideration different risk factors as well as economic variables for calculating the cap rate. Some of these economic variables are illustrated in **Error! Reference source not found.**.

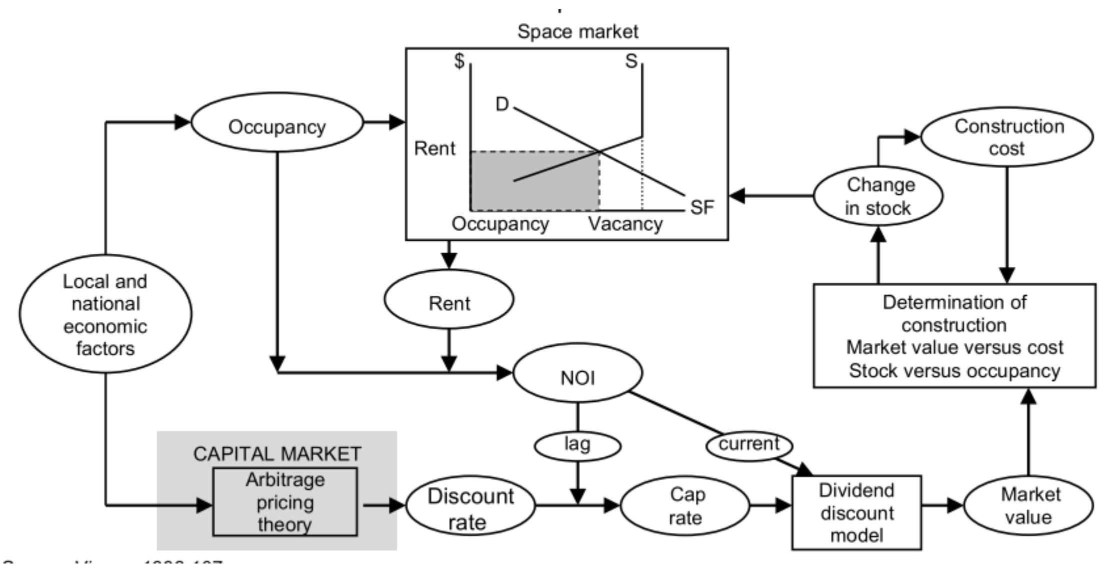

Figure 3.1The REEFM model (Viezer, 1998; Boshoff 2013a).

Boshoff (2013a) explains the REEFM model in detail. In summary, the model is a recursive model, consisting of six stochastic equations (occupancy, real rents, capitalisation rate, market value per unit, change in stock, and real construction costs) plus seven deterministic equations (a net operating income proxy, market value per unit, stock of space, vacancy rate, implicit appreciation market return, implicit income market return and implicit total market return).

The six stochastic equations given by Viezer (1999) are all in the format:

$Yi = \alpha i + \beta 1Xi + \varepsilon i$ **Equation 3.2**

where:

αi = Y intercept for the population;

$\beta 1$ = slope for the population;

εi = random error in Y for observation i.

The stochastic equations all have the format of the above equation considering the variables affecting the dependent or real estate variable. The econometric modelling of the rent using the demand and supply interactions of the property market forms a basis for forecasting. The limitations of these models are, however, that they focus on explaining the present state of the real estate market without giving much information on the future directions. This informs the attempts of this study to employ the use of economic leading indicators as commonly seen in turning point analysis to detect turning points in indirect property data series. It supports further investigation of this approach to modelling the relationship between economic leading indicators and the commercial real estate market in South Africa and Nigeria.

Most important is the need to assess the capability of this model to evaluate the probability of a shift or change in the direction of rent in these markets, thus adding to the possibility of detecting or developing warning signals from macroeconomic time series data.

3.2. Statistical approaches and their usefulness in identifying leading indicators

Several rules and methods have been employed for identifying leading indicators and their relationships with the real estate market. These include the standard causality and switching regime models to binary models. The Granger causality test was employed in Ashuri and Shahandashti (2012) for testing the leading capability of economic variable in forecasting Construction Cost Index (CCI).

Frankel and Saravelos (2012) employ a literature review method for selecting leading indicators. The review suggests that central bank reserves and past movements in the real exchange rate were the two leading indicators. This approach has its limitations in that the criteria for selection is subject to the researcher's judgement and might not be a recommended approach for practical purposes where investment decisions must be made and justified.

Although expert judgement could facilitate selection of leading indicators, a statistical basis for selection has also been encouraged. Testing these indicators through uniform standardised statistical approaches ensures that the process of modelling can be replicated across differing economic time series in Africa.

Baba and Kisinbay (2011) proposed a formal econometric method to identify leading indicators from a large data set. They suggested that less emphasis be placed on some traditional indicators, such as the real money supply, which had not performed well as a leading indicator of recessions in recent cycles. Their main arguments for formal statistical and data-based selection approaches was the fact that such approaches are easily replicated, applicable to a large data set and flexibility for various users. This brought inclusiveness to the process of investment analysis where data becomes consistent, available and useful to all levels of users or stakeholders.

This approach to selecting leading indicators also allows for uniformity in reporting and data presentation and, subsequently, standardisation of the real estate investment process across various African markets.

The forecasting process in investment analysis can significantly eliminate random errors if it:

1. Maximises the signals provided by indirect property data in the financial markets;
2. Improves analysis using warning signals from the macro economy to position capital flow and investment decisions;
3. Employs statistical approaches to selecting the combination of leading indicators for forecasting models.

The base selection of indicators cuts across those from the standard leading indicators and leading indicator series developed by private institutions. The leading capacity of the indicators is an important metric for acceptability. Krystalogianni, Matysiak and Tsolacos (2004) employed the standard causality in selecting leading indicators.

Other discussions about leading indicator selection methods, recommend the Granger causality or the Chi Square. (See Ashuri and Shahandashti, 2012). The encompassing algorithm as seen in Baba and Kisinbay (2011) is another example of statistical approaches to selecting leading indicators. After selecting the leading indicators, the study can proceed to forecast and model the relationship between the rent variable and indicator series. An argument for simplicity in modelling favours the application of causality tests for the selection process.

3.3. The turning point analysis

A turning point analysis refers to the methods for detecting the cyclical behaviour of business indicators. The history of turning point analysis has its background in the early works of

Burns and Mitchell in 1946. Artis, Bladen-Hovell, Osborn, Smith and Zhang (1995) as well as Anas and Laurent (2004) are a few others who have explored the use of turning points in dating business cycles.

A turning point analysis is done by using a regression probability model that outputs a dichotomous binary result that can be either 1 or 0. The threshold for turning point detection is typically set at the 50% or 0.5 threshold. Anas and Laurent (2004) employed a 50% threshold to signal a recession in a series. The decision rule indicates a decline when the assessed probability is lower than the threshold value of 50%. A decision check is vital to decide whether or not a turning point has occurred.

In this study the decision rule is the determination of a threshold over which the probability of a turning point is understood as a signal. Hamilton (1989) recommended a 50% threshold in the formula:

$P\ [St = 0] > 0.5$

In the Neftçi method a limit of 90% or 95% is, however, suggested. Hamilton indicated the rule that a reduction phase is detected at time t, if $Pr\ (zt = 1|\{\Delta yt\}\ T$ for $Pr\ (zt = 1|\{\Delta yt\}\ Tt=1) > 0:5$.

Once the data have been segmented in this way, the series takes the value of 1 in expansion and 0 in contractions. At the threshold set, the amount of the model that is explained by the independent variables provides insight into their predictive capacity as leading indicators.

We would have the algorithm:

peak at $t = \{Pr\ (zt+1 = 1|\{\Delta yt\}\ Tt=1) < 0.5;\ Pr\ (zt = 1|\{\Delta yt\}\ Tt=1) > 0.5\}$;

trough at $t = \{Pr\ (zt+1 = 1|\{\Delta yt\}\ Tt=1) > 0.5;\ Pr\ (zt = 1|\{\Delta yt\}\ Tt=1) < 0.5\}$:

Despite the argument for varying threshold values, the 50% threshold has a long history of usage and acceptability. This becomes especially useful when deciding the best approach between a parametric or nonparametric model.

Harding and Pagan (2002) compared the use of a parametric and nonparametric approach to detecting and dating cycles. They favour the use of a nonparametric approach based on the transparency it offers. They further explain that since the subject of dating a cycle is essentially one of data summary, it is reasonable to employ methods that are as non-parametric as possible.

Anas and Laurent (2004) reported that several nonparametric models for detecting turning points had been developed, based on the parametric Markov-Switching model by Hamilton. This makes the Hamilton decision rule a significant basis for any further assessment of the nonparametric model we consider in this study.

Tsolacos, Brooks and Nneji (2014) also compared the Probit and a Markov switching model for their accuracy to forecast the signs of future rental growth in four key United States commercial rent series. They concluded that the Probit model was preferable as it can detect signals of an impending change in market behaviour well in advance because of the directional result it yields relative to the threshold rule set. The Probit model is proactive in detecting signals that can guide investment behaviour.

3.4. Modelling approaches

Frankel and Saravelos (2012) summarised the modelling approaches used in previous literature on predictive indicators; the linear regressions (Probit or Logit techniques), non-parametric methods, a third approach that involves qualitative and quantitative methods which groups countries into crisis and non-crisis control groups and finally the use of Artificial Neural Networks (ANN), Genetic Algorithms (GA) and Markov Switching Models.

They found that the artificial neural networks approach to forecasting was too volatile and might not be suitable for economic data series. Munusamy *et al.* (2015) concluded in their research that the most used forecasting models were explanatory and exploratory forecast models. They suggested that the most crucial feature of the model was the ability to eliminate nonlinearity as can be found in the use of artificial neural networks (ANN). However, they also recommend the use of Logit models in combination with a Markov regime switching. This is due to the level of uncertainty that is allowed in the ANN modelling and simulation forecasting. Analysts might have a difficult time deciding whether to choose a model for how much of the market variations it explains over the accuracy of the model's predictions.

Krystalogianni, Matysiak and Tsolacos (2004) also employed the Probit model to evaluate the leading indicators in a United Kingdom market owing to their ability to predict negative or positive movements in the market. The forecast performance was found to be satisfactory. The leading indicators were selected on the basis of series developed by private organisations and the United States conference board series. According to their report the predictability of lasting directional changes in real estate performance represents a useful tool for real estate investment decision-making. Their defence for the use of the Probit or Logit models supports other studies following the school of thought that recommends the use of turning point forecasts through the Logit model.

Identifying leading indicators within the framework of such models potentially creates huge opportunities for investment and finance in Africa's real estate market. The research by Krystalogianni, Matysiak and Tsolacos (2004) suggested that the Probit model is widely used for assessing turning points predictability using leading indicators. Their studies supported the identification of a leading indicator within a Probit model for assessing turning points and consequently the probability of negative or positive movements in the real estate market. They also worked with markets within developed economies. This leaves room for testing the applicability of these models with data from South Africa and Nigeria.

There is little reference to how these models would perform in developing or emerging economies. However, the results of their study provided the basis for the assumption that the Probit model can be investigated further in view of its applicability in emerging markets with their unique limitations of data availability and access.

In another study by Tsolacos (2012) the researcher employed the Probit model for predicting turning points across three markets and the results proved useful for complementing judgement and other linear forecasting methods. His emphasis was placed on identifying indicators with a capacity to predict turning points. Using the identified leading macroeconomic indicators and nonparametric models, an improved accuracy of forecasting turning points could be achievable.

The probit model reflects a negative or positive probability for the rent growth variable; this leading period could be between the first or fourth quarter ahead. This duration of the forecast provides a significant amount of information in view of investment decisions. An understanding how this model works regarding indirect property data in South Africa and Nigeria will offer a major addition to the body of knowledge on modelling the relationship between the leading indicators and the real estate market. Tsolacos (2012) modelled the leading relationship using a Logit model in a regression analysis. The Logit or Probit model is similarly used for modelling turning points in the business cycle. In this relationship, the dependent variable is a dichotomous variable whose value is either 0 or 1 to reflect whether the economy is in a recession or expansion.

Four models were considered for predicting or modelling the movement of commercial share prices which lead the business cycle. These were the probit or logit which had been used interchangeably in literature, moving averages which is similar to the weighted averages such as seen in Roland Igbinoba Housing Index (no date), Vector autoregression models (VAK) and, lastly, lagged changes in the commercial share price index. The relative high performance of the Logit model is the reason why it was selected for this study.

3.5. The Probit and Logit regression models

This study is similar to the illustrated Probit approach in Krystalogianni, Matysiak and Tsolacos (2004). The applicability and use of the Probit modelling technique in developed economies such as in the United Kingdom opens the possibility of even further research for markets with sparse transaction data. This nonparametric approach for detecting turning points is becoming a popular approach for evaluating future direction in rent growth. In their report, Krystalogianni, Matysiak and Tsolacos (2004) showed that a Probit model is deployed to compute probabilities that a contraction (T) in capital values will occur at given values of a set of leading indicator variables (x).

A variable T is defined so that:

T = 1 for the period that capital values decline

T = 0 otherwise

Therefore, the objective of using a Logit approach is to estimate a response probability:

$\Pr(T = 1|x) = \Pr(T = 1|\ x1, x2, ..., xk)$ **Equation 3.3**

where x denotes the full set of explanatory variables (x1, x2, ..., xk).

The underlying analytical process for analysts recommended in this study is explained in three stages:

1. Identifying the appropriate macroeconomic leading indicators for input in a Probit model.
2. Applying a probabilistic modelling approach to determine the possibility of turning points given a specified threshold.

3. Determining the lead period and predictive capacity of this model and how much variation in the dependent variable is explained by the lead indicators introduced in the econometric model.

According to Krystalogianni *et al.* (2004), although rising probabilities signal a turning point in capital values, a threshold level of these probability estimates must be selected in order to formally determine whether these probabilities constitute a prediction of a phase of declining (increasing) capital values. If the forecast probability exceeds this threshold value, a phase of sustained decline in capital values is predicted. It is then possible to determine the number of contractions that were predicted, the number that were not predicted (Type I error) and the number of times a prediction was made and there was no decline in capital values (Type II error).

There is typically no real difference between the results from a Probit or a Logit regression model, hence they are used interchangeably. Tsolacos, Brooks and Nneji (2014) describe them as a family of models, implying the inherent similarity in outcomes. They are also used interchangeably in Tsolacos and Brooks (2010); Michael and Almeida (2016); and Moolman and Jordaan (2005).

In their study, Moolman and Jordaan (2005) proposed the use of turning point analysis in detecting business cycles within the South African market. They considered four potential models for predicting the direction of the commercial share price index: These are Logit, moving averages, the vector autoregression (VAK) model and evaluation of lagged changes. They found that the Logit model performed relatively well in predicting the direction of the commercial share index both in in-sample and out-of-sample data.

The Logit model indicated a decline in commercial share prices when the probability of a downturn in the commercial share price index exceeded 50%, while it is assumed to indicate an upturn in commercial share prices when the probability of a downturn in the commercial share price index is below 50%.

3.6. The Probit and Logit regression for real estate forecasting

Tsolacos and Brooks (2010) predicted that future real estate research would focus on identifying early signals in both the occupier and investment markets. They described the relationship between securitised real estate and the direct market as a basis for this future direction. The understanding of price adjustments in the indirect real estate market was found to affect price discovery in the direct real estate market. This placed the focus on REIT and listed property data.

The evaluation of real estate pricing is experiencing major improvements. Securitised real estate information and its relationship with leading indicators have become a critical part of the forecasting process. Leading indicators have become part of a larger body of economic and financial analysis that can be applied to real estate. There is also a large body of work on turning points. The models employed in this research improve on the rent model using leading indicator series as basis for detecting turning point.

The Probit and Logit models detect the probability of turning points in the future, based on the past. These econometric models have the goal of identifying forthcoming turning points and establishing probabilities for such occurrences. These models' sometime referred to as limited dependent variable models, work with a dependent or outcome variable that is dichotomous depicted as 1 or 0. This would translate to a dichotomous output of 1 or 0 as an indication of the probabilities of turning points in rent growth figures. When $Y = 1$ indicates the probability of a negative growth, while $Y = 0$ indicates the probability of a growth in rental values. The probabilities rise accordingly, the closer the series comes to a turning point, for example a series of leading indicators influencing a dichotomous rent variable in

South Africa. Input of the exponents of these variables into the Logit or Probit regression model will output probability estimates that determine how likely a turning point in the real estate market is.

Tsolacos, Chris and Ogonna (2014) investigated episodes of negative and positive rent growth using four United Kingdom leading indicator series; the Conference Board Leading Economic Index (CBLEI), a consumer confidence index (UMCSI), the OECD leading indicator (OECDLEI) and the NAREIT All-REIT index (REIT). They assumed an indirect linkage between REIT prices and expected rent changes. This linkage forms the basis for investigating rent forecasting by using the Probit and Logit models. Probit models use signals from leading economic indicators to forecast the probability of two possible states of the rental or capital value variable – that is, periods of declining and rising values. This makes them useful for markets with infrequent capital flow and transaction data. The Probit and Logit models focus on the detection of turning points in rent growth to plan future purchases and capital flow. Future rent adjustments ultimately affect the valuations and appraisals of today in the evaluation of risks and, consequently, yield calculations.

The model input variables which present the leading series, have a direct influence on the occupier and investment market, because investors and occupier expectations are on most occasions gauged by using the signals from these series. Binary predictions are of greater practical use than point forecasts when the objective is simply to know the probability that a series will either rise or fall, without the additional complication of a point forecast (Tsolacos, Brooks and Nneji, 2014). In this study focus was given to the Logit regression model as the predictive approach to modelling the relationship between the binary outcomes of the listed or commercial real estate market movements and the macroeconomy. The transformation of listed real estate data to binary outcomes of Y = 1 (decline), and Y = 0 (growth), is regressed against selected macroeconomic indicators using a logistic regression.

The Logit model is represented by:

$Y_{t+k}= \alpha_t+ \beta_t * X_t + \varepsilon_t$ **Equation 3.4**

$Rt = 1$ if $Yt> 0$

Yt = An unobservable factor that determines the occurrence of a recession

t = time

k = length of the forecast horizon

ε_t = A normally distributed error term

X_t = The value of the explanatory variable at time t.

Rt = observable recession

The parameters α and β are estimated with maximum likelihood.

3.7. Chapter summary

In this chapter, rent modelling was discussed with regard to the demand and supply side of linear regression models. It first focused on discussing the use of leading indicator series to model the signals from the economy and the effect of this on rent growth. Following this, the chapter described the development of turning point analysis as a probabilistic forecasting technique that is useful in markets with sparse transaction data. The chapter introduced the structure and design of the Logit or Probit models which combine the detection of turning points with leading time series data as part of the modelling process. The final section described how this modelling process was applied to rent growth forecasting in real estate markets.

CHAPTER 4.

DATA AND RESEARCH PROCEDURES

4.0. Introduction

The collection and use of quantitative data provide resolutions to the research questions raised in the first chapter of this report. In this chapter, the procedures for data gathering, treatment and analysis are presented. The chapter is consequently divided into six (6) parts, including Section 4.1, which provides a brief overview of the data and collection process. In Section 4.2 the difference between the data periods used for Nigeria and South Africa are discussed. Section 4.3 explores the variables in the analysis. Section 4.4 explains data sources and descriptive statistics, Section 4.5 describes data limitations, and lastly, Section 4.6 provides a summary of the chapter.

4.1. Data

Data collection methods and parameters are drawn from the literature reviewed. South African economic data were collected from the Iress expert database and Statistics South Africa (Stat SA) database. The FTSE/JSE SA Listed Property (J253) consists of the twenty largest liquid companies by market capitalisation in the Real Estate Investment and Services Sector and Real Estate Investment Trust Sector with a primary listing on the JSE. FTSE/JSE SA Listed Property (J253) quarterly price data were extracted from the Iress Expert database.

Nigerian listed real estate data that were collected from the Central Bank of Nigeria, Sky Shelter REIT (SKY REIT) and the UACN property development company data. The duration of transaction in data reflect more than five years of pricing and therefore best represent the listed commercial real estate. Olanrele *et al.* (2019) noted the limitation of using other Nigerian REIT (N-REIT) data such as Union Home, Smart Products Nigeria Plc (SMURFIT) and UPDC REIT which were only recently established. The weighted average of Sky Shelter REIT (SKY REIT) and the UACN property development company data served as proxy for the listed real estate sector.

All monthly data were converted into quarterly data prior to analyses to ensure data uniformity with the exogenous data.

The model was accordingly tested using four (4) performance measures including:

1. The chi-square and significance level;
2. The omnibus test of model significance;
3. Cox & Snell R-square and Nagelkerke R- square; and
4. Hosmer-Lemeshow test.

Chi-square and Sig: The model's chi-square statistic and its significance level present the first test of model performance. A significant p-value is compared to a critical value, perhaps .05 or .01 to determine whether the overall model is statistically significant. The value given in the Sig. column is the probability of obtaining the chi-square statistic, given that the null hypothesis is true.

The omnibus test for model significance: This is a test for the performance of the independent variables over the null model with only the intercept. This test evaluates how much of the variance in the dependent variable is explained by changes in the independent variables.

Cox & Snell R-square and Nagelkerke R-square: These are pseudo R-squares. These R-squared values test the model's goodness of fit. The Cox & Snell R 2 can be interpreted like the R-squared in a multiple regression but cannot reach a maximum value of 1. The Nagelkerke R-squared can reach a maximum of 1.

Hosmer-Lemeshow test: A second test for the model's goodness of fit is the Hosmer-Lemeshow. This tests the null hypothesis that predictions made by the model will fit perfectly with observed group memberships. The higher the value of this test the better the goodness of fit.

This discussion also compares the results of the four (4) performance measures across the Nigerian and South African markets. This aims to answer the attendant question of comparability of models used across the two emerging markets in order to establish the best performed in this analysis.

4.2. Data periods

There was a limitation on the selection of time series for dependent and independent variables, in that the longest series available for South African data was from Quarter 1 of 2003 till Quarter 4 of 2018. This implied that other series not meeting up to this range were invalid for consideration. Missing data for quarters not exceeding 1-5 quarters were replaced with the closest available data.

The period chosen was between the first quarter of 2003 and the fourth quarter of 2018. The available data for the Nigerian listed real estate market were collected for the period 2008 Q1 to 2018 Q4. The South African macroeconomic data series were collected for the same period.

4.3. Variables

The Iress Expert Database provided the three top real estate instruments, including FTSE/JSE Property Loan Stock (J256), FTSE/JSE Real Estate Investment Trusts (J867) and FTSE/JSE SA Listed Property (J253). The FTSE/JSE SA Listed Property (J253) proved to be the only real estate variable spanning up to the required fifteen years as suggested in Jadevicius, Sloan and Brown (2013).

The availability of data spanning the required period served as a basis for selecting the real estate time series to adopt as the dependent variable. The FTSE/JSE Property Loan Stock (J256) and FTSE/JSE Real Estate Investment Trusts (J867) were thus excluded from the analysis.

The South African macroeconomic data or independent variables that the author evaluated, included the GDP at market prices (R million), percentage CPI consumer prices (CPI) excluding food and non-alcoholic beverages and fuel (all urban areas), manufacturing (2015=100), leading indicator (2015 = 100), coincident indicator (2015=100), lagging indicator (2015=100), Nominal M0 Money Supply (M0), Nominal M1A Money Supply (M1A), Nominal M1 Money Supply (M1), Nominal M2 Money Supply (M2), total monetary (M3) deposits, exchange, interest rates and the gold price. Nigerian macroeconomic variables included, total GDP, the prime lending/interest rate (%), treasury bill rate (%), total money asset, money supply (M1), currency in circulation, and money supply (M2).

The leading indicator (2015 = 100), coincident indicator (2015=100), lagging indicator (2015=100) are further explained in Van Der Walt and Pretorius, (2004) as follows:

The leading indicator series is composed of: Opinion survey of volume of orders in manufacturing, Opinion survey of stocks in relation to demand: manufacturing and trade, Opinion survey of business confidence: manufacturing, construction and trade composite, Leading business cycle indicator of major trading-partner countries: percentage change over twelve months, Commodity prices in US Dollars for a basket of South Africa's export commodities: six-month smoothed growth rate, Real M1 money supply (deflated with the CPI): six-month smoothed growth rate, Prices of all classes of shares: six-month smoothed growth rate, Number of residential building plans passed for flats, townhouses and houses larger than $80m^2$, Interest rate spread: 10-year bonds less 91-day treasury bills, Gross operating surplus as a percentage of gross domestic product, Labour productivity in manufacturing: six-month smoothed growth rate, Job advertisements in the Sunday times newspaper: six-month smoothed growth rate, Opinion survey of the average hours worked per factory worker in the manufacturing sector

The Coincident indicator series is composed of: Gross value added at constant prices, excluding agriculture, forestry and fishing value of wholesale, retail and new vehicle sales at constant prices utilisation of production capacity in manufacturing total formal non-agricultural employment industrial production index.

The Lagging indicator series is composed of: Employment in Non-Agriculture sector, Total number of hours worked by production workers in the construction sector, Physical volume of mining production of building materials, Value of unfilled orders as percentage of sales in manufacturing, Value of fixed investment in machinery and equipment, Value of non-residential buildings completed, Value of commercial and industrial inventories at constant prices, Labour cost per unit of the physical volume of manufacturing production.

The Nigerian REIT and JSE time series data are used to create dummy binary outcomes for the purpose of logistic regression. The time series data difference of $Y_t - Y_{t-1}$ were classified based on a rise or fall. A growth in the time series represented a 0. While a fall represented a 1. This provided the data for the Binary Variable in both data sets. The South African dummy variable is denoted as, South Africa Listed Real Estate (SALRE), while the Nigerian dummy variable is denoted as Nigeria Listed Real Estate (NLRE)

4.4. Descriptive statistics of data

The indicators identified in the literature review were examined for preliminary selection of the independent variables and the dependent variable was assessed and the summary statistics are shown in **Error! Reference source not found.** to **Error! Reference source not found.**.

Table 4.1 Descriptive Statistics of South African data employed in Logit analysis

	Minimum	Maximum	Mean	Std. Deviation
FTSE/JSE SA Listed Property (J253)	24905288373	585250954031	196738877374	161566289587
South Africa Listed Real Estate (SALRE)	0	1	.70	.460
GDP @ market prices (R million)	317548.00	1236403.00	743515.90	283143.52
Percentage CPI Consumer prices: CPI excluding food and non-alcoholic beverages and fuel (all urban areas)	-11.20	9.20	4.33	3.09
Manufacturing (2015=100)	87.77	108.40	98.22	4.32
Leading indicator (2015 = 100)	86.87	108.40	102.10	4.49
Coincident indicator (2015=100)	69.43	103.67	90.68	10.28
Lagging indicator (2015=100)	94.53	124.37	101.37	6.46
M0	59579.67	250307.67	144681.46	60638.57
M1A	220759.67	848555.67	501334.74	202849.47
M1	395897.00	1726139.67	947969.44	413235.46
M2	746724.33	2830701.67	1704159.54	640799.34
Total monetary (M3) deposits	833366.00	3508983.00	2090677.05	818284.46
Interest rates	25.50	51.00	32.56	6.31
Price of gold per ounce (rand)	7664.75	56662.66	30071.49	16290.20
Exchange rates	212.05	312.30	267.04	24.21

Table 4.2 A descriptive table of the independent variables and their unit of measurement, correlation to SA listed real time series, characteristics and data-level

Variable	Unit of Measurement	Correlation	Characteristics	Level
GDP at market prices	Rands (R)	Positive (S)	Economic performance	National
Percentage CPI Consumer prices:	Percentage (%)	Positive (W)	Price Index	National
Manufacturing	Index (2015=100)	Positive (W)	Capital production level	National
Leading	Index (2015=100)	NIL	Economic indicator	National
Coincident indicator	Index (2015=100)	Positive (S)	Economic indicator	National
Lagging indicator	Index (2015=100)	Negative (W)	Economic indicator	National
M0	Rands (R)	Positive (S)	Money supply	National
M1A	Rands (R)	Positive (S)	Money supply	National
M1	Rands (R)	Positive (S)	Money supply	National
M2	Rands (R)	Positive (S)	Money supply	National
Total monetary (M3) deposits	Rands (R)	Positive (S)	Money supply	National
Interest rates	Percentage (%)	Positive (M)	Cost of capital	National
Price of gold per ounce (rand)	Rands (R)	Negative (S)	Capital market performance	National
Exchange rates	Rands (R)	Positive (M)	Capital market performance	National

Table 4.3 Descriptive Statistics of Nigerian Data Employed in Logit Analysis

	N	Minimum	Maximum	Mean	Std. deviation
NSE Listed Property Index	44	4145.10	4921.11	4548.48	227.73
Nigeria Listed Real Estate (NLRE)	44	0	1	.50	.506
Total GDP	36	12583478.33	35230607.63	22098650.22	5959960.915809
Prime lending/interest rate (%)	44	44.65	58.27	50.72	3.11
T-bill %	44	5.12	44.10	27.94	10.65
Total money asset	44	21542374.30	97307716.20	54437047.19	22378043.23
Money supply (M1)	44	11801598.20	33680739.24	21257092.87	6650841.91
Currency in circulation	44	2624429.50	6385845.91	4455189.75	1015721.20
Money supply (M2)	44	21542374.30	78588158.53	47817724.05	16402868.45

Correlation with the JSE listed real estate data = (S) Strong >70%, (M) Medium = 30-70%, (W) Weak <30%

Table 4.4 A descriptive table of the independent variables and their unit of measurement, correlation to Nigerian listed real estate time series, characteristics and data-level

Variable	Unit of measurement	Correlation	Characteristics	Level
Total GDP	Naira (N)	Positive (M)	Economic performance	National
Prime lending/interest rate (%)	Percentage (%)	Negative (W)	Cost of capital	National
T-bill %	Percentage (%)	Positive (M)	Risk-free rate	National
Total money asset	Naira (N)	Positive (M)	Money Market Indicator	National
Money supply (M1)	Naira (N)	Positive (M)	Money Market Indicator	National
Currency in circulation	Naira (N)	Positive (M)	Money Market Indicator	National
Money supply (M2)	Naira (N)	Positive (M)	Money supply	National

Correlation with the NSE listed real estate data = (S) Strong >70%, (M) Medium = 30-70%, (W) Weak <30%

4.5. Limitations for replicating model using Nigerian data

Nigerian REIT time series data found, included Union Homes, Skye Shelter and UACN Properties. The historical data available covered ten years as compared to fifteen years' data that were collected for South Africa. Relative to the Nigerian data, the analysis examines the Nigerian Stock Exchange (NSE) instruments for the availability of a commercial real estate data series. The NSE Listed RE Index developed, is proxy for the listed real estate indicator that was not provided in the Nigerian Stock Exchange index database.

4.6. Chapter summary and conclusion

In this chapter, the data that were collected, was explored and described to provide a background for the analysis to follow in Chapter 5. In order to replicate results adequately, the sources and variables or indicators selected for analysis were explained. Descriptive statistics regarding the data collected were provided and the limitation of the data set was discussed. In the next chapter, the collected data will be analysed to realise the objectives of the research.

CHAPTER 5.

DATA ANALYSES AND DISCUSSION

5.0. Introduction

This chapter provides empirical evidence relative to the stated objectives in Chapter 1. Thus, apart from Section 5.1, which provided brief introductory remarks, the remaining sections are divided into five sections, including, Section 5.2 which contains analysis on the economic indicators for modelling and forecasting of commercial real estate rental values in the two countries. Section 5.3 deals with analysis relating to the performance of predictive models in identifying market indicators for the Nigerian and South African real estate market, Section 5.4 focuses on developing the forecasting models for early detection of turning points in commercial real estate rental values in Nigeria and South Africa, Section 5.5 provides a comparison of model performance relative to identifying leading economic indicators in Nigeria and South Africa and Section 5.6 concludes the chapter.

5.1. Economic indicators for modelling and forecasting of commercial real estate rents

In this section, reliable market indicators for commercial real estate forecasts were identified for both the Nigerian and the South African markets, thus the analysis was done separately for each of the markets, because as expected, market indicators are not the same for all markets. The analysis begins with the identification of market indicators for the South African real estate market, while the analysis for the Nigerian market follows immediately after that.

5.2. Economic indicators for modelling and forecasting of commercial real estate rents in South Africa

The indicators of economic expectations or economic indicators identified were selected from previous related studies. These included fourteen major lead indicators, including CPI, GDP, manufacturing production, exchange rate, interest rate and money supply. Therefore, in identifying reliable indicators for forecasting commercial real estate rents in the two countries, the Pearson and Spearman correlation test was employed in this analysis.

The data used in the earlier part of this section focused significantly on the South African property market. Inferences and recommendations are consequently based on results from South African economic data. The research only worked with publicly available data, especially because the results of this analysis are expected to be simple enough to be used by industry investors who may not rely on transaction or primary survey data for assessment of investment decisions. The first test carried out, was the bivariate correlation analysis. In the test for correlation across variables, the Pearson and Spearman correlation was included to account for the categorical or binomial nature of the dependent variable in the Logit regression model. The comparison does not show significant difference in the outcomes. Values for the Spearman correlation agree with the Pearson correlation values. The results are summarised in **Table 5.1**.

Table 5.1 Spearman correlation of South African economic indicators with the dependent listed real estate variable

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

			FTSE/JSE SA listed property (J253)	GDP at market Prices (R million)	% CPI	Manufacturing (2015=100)	Leading indicator (2015 = 100)	Coincident indicator (2015=100)	Lagging indicator (2015=100)
Spearman's rho	FTSE/JSE SA listed property (J253)	Correlation coefficient	1.000	.984**	.342**	.450**	.230	.948**	-.471**
		Sig. (2-tailed)	.	.000	.006	.000	.067	.000	.000

Table 5.1. Continued, Spearman correlation of South African economic indicators with the dependent listed real estate variable

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

			M0	M1A	M1	M2	Total monetary (M3) deposits	Interest rates	Price of gold per ounce (rand)	Exchange rates
Spearman's rho	FTSE/JSE SA listed property (J253)	Correlation coefficient	.986**	.986**	.987**	.984**	.985**	.591**	-.974**	.580**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
		N	64	64	64	64	64	64	64	64

In identifying reliable indicators for modelling the probability of turning points, this study tested the relationship between economic variables and the listed real estate variable. In the correlation **Error! Reference source not found.**, the P-value of less than 0.05 indicates a significant relationship between the economic variables and the listed real estate variable. A significant p-value implies that a significant relationship exists between the economic variable and the listed real estate series. Thus, **Table 5.1** shows the results of the correlation analysis of the independent variables and the dependent variable. In this analysis, the FTSE/JSE SA listed property (J253) variable was tested against fourteen leading indicator series including:

1. The GDP at market prices;
2. Coincident indicator;
3. Leading indicator;
4. Lagging indicators;
5. Money supply indicators; M0;
6. M1A;
7. M1;
8. M2;
9. Total monetary deposits M3;
10. Gold price per ounce;
11. Rand exchange rates;
12. Interest Rates;
13. Manufacturing (2015=100); and
14. Percentage CPI consumer prices.

The correlation analysis provided the basis for selecting the macroeconomic indicators that were regressed against the binomial dependent variable. The macroeconomic factors that indicate significant relationship with FTSE/JSE (i.e. SA listed property) can explain FTSE/JSE changes.

All money supply variables show a significant P-value at the 0.05 level as seen in **Table 5.1**. This proves the existence of a statistically significant relationship between the listed real estate variable and the M0, M1, M1A, M2 and M3 variables. M0 shows similar R-values for the Spearman correlation at 0.986 as the Pearson correlation of 0.959. It is significant at the 0.05 level. There is a strong positive correlation with the listed real estate indicator.

Similarly, the M1A Spearman and Pearson as seen in **Table 5.1** are 0.986 and 0.996 respectively and a significant P-value < 0.05 indicates the existence of significant influence of the independent variable. In **Table 5.1**, the M1 demonstrates a correlation R-value of 0.987 for Spearman's correlation and a slightly lower 0.967 for Pearson's correlation. The M1 variable's P-value is also significant at the 0.01 level. The M2 variable as seen in **Table 5.1** also shows a significant value of < 0.05 and the coefficient of correlations indicates strong positive correlations at 0.984 for Spearman r and 0.942 for Pearson r.

The M3 variable in **Table 5.1** shows the largest difference between the Spearman r and the Pearson r which are 0.985 and 0.928 respectively. It also shows a two-tailed significance level of > 0.01. All money supply variables were found to be significant predictors for the Logit regression model. This was to be expected, given that real estate is a capital-intensive venture. The listed real estate instruments, being a significant source of financing for actual real estate supply, are affected significantly by the money supply. Simo-Kengne, Balcilar, Gupta, Reid and Aye (2012) also agreed that monetary policy is not neutral, as house prices decrease substantially as a result of a contractionary monetary policy.

Interest rate also showed a significant P value of 0.000 > 0.05, Spearman and Pearson correlation coefficients of 0.591 and 0.497, which are average degrees of correlation. The data in Tables 5.13 and 5.14 suggest that the cost of capital has a moderately strong positive relationship with the listed real estate market. Higher cost of capital implies increasing risk for direct real estate investment, which makes indirect real estate an attractive alternative. Indirect or listed real estate instruments would appreciate as the increasing costs of capital implies that developers would require other sources of capital than bank loans.

GDP at market price indicated a significant relationship with the dependent FTSE/JSE J253 indicator on the 0.01 level as seen in Table 5.1. It also showed a strong positive correlation coefficient both on the Pearson and Spearman rho. The Gross Domestic Product has a strong correlation coefficient of 0.948 which presents it as a strong economic indicator for price discovery and forecasting the listed real estate market. As production increases, economies tend to experience growth in employment and subsequent demand for commercial office space.

The Consumer Price Index (CPI) indicator as seen in Table 5.1 was not significant on the 0.05 level. Its coefficient of correlation was, however, relatively low with 0.342 on the Spearman R-value and 0.273 on the Pearson correlation. This indicates a no significant level of relationship between the CPI and the dependent variable, and a low correlation. In this case, a relationship between product prices or inflation and the listed real estate market was not established.

Similarly, manufacturing showed R-values of 0.450 and 0.397 on the Spearman and Pearson correlation coefficients. Despite showing significant value, the P-value > 0.01; these variables show weak correlation with the dependent variable.

The FTSE/JSE SA listed property (J253) showed a positive correlation with the GDP at a 0.05 level of significance. The GDP, being major economic indicators, is bound to affect the spending capacity and general sentiments regarding long-term investment in commercial real estate. A growing GDP would signify growing interests in commercial properties, offices, warehouses, shopping centres and serviced apartments. The coincident, lagging and leading indicators were also tested for correlation and the levels of significance as regards the dependent variable as seen in **Table 5.1**

The leading indicator failed to show any level of significance with the P value being $> 0.05 > 0.01$. This, rules out the existence of any linear relationship between the leading indicator and the listed property data. The business leading indicators have been criticised in regard to their accuracy and reliability as seen in Boshoff and Binge (2019). The coincident indicator was significant on the 0.01 level and showed a Pearson correlation value of 0.842 and a corresponding higher Spearman correlation value of 0.948.

A weak negative correlation was recorded for the lagging indicator. The Pearson correlation value was -0.420 while the Spearman correlation value was -0.471. The lagging indicator was also significant on the 0.01 level. The price of gold per ounce showed a significance level of < 0.01 and a strong negative correlation; -0.974 for the Spearman correlation and -0.929 for the Pearson correlation. These business indicators within the South African context are relevant for confirming the direction of the overall economy. Business sentiments are significant drivers of real estate investment and the negative signs suggest that a growth in these indicators might adversely affect investment in listed real estate.

The exchange rate was significant on the 0.01 level; the Pearson correlation coefficient was 0.531 and the Spearman correlation was 0.580. A strong positive correlation with the exchange rate indicates that a strong growth in FDI and a demand for local currency or other expansionary foreign policies would stimulate growth in listed real estate markets.

Table 5.2 Test for multicollinearity across South African independent variables data sets

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

		FTSEJSE SA listed prop. J253	GDP R million	Percen-tage CPI	Manufactur-ing (2015=100)	Leading indicator (2015=100)	Coincident indicator (2015=100)	Lagging indicator (2015=100)	M0
FTSE JSE listed property J253	Pearson correlation	1	.948**	.273*	.397**	.134	.842**	-.420**	.959**
	Sig. (2-tailed)		.000	.029	.001	.292	.000	.001	.000
GDP R million	Pearson correlation	.948**	1	.385**	.394**	.214	.920**	-.375**	.998**
	Sig. (2-tailed)	.000		.002	.001	.090	.000	.002	.000
Percentage CPI	Pearson correlation	.273*	.385**	1	.318*	-.153	.489**	.380**	.373**
	Sig. (2-tailed)	.029	.002		.010	.228	.000	.002	.002
Manufacturing (2015=100)	Pearson correlation	.397**	.394**	.318*	1	.471**	.656**	.155	.394**
	Sig. (2-tailed)	.001	.001	.010		.000	.000	.221	.001
Leading indicator (2015=100)	Pearson correlation	.134	.214	-.153	.471**	1	.330**	-.453**	.189
	Sig. (2-tailed)	.292	.090	.228	.000		.008	.000	.135
Coincident indicator (2015=100)	Pearson correlation	.842**	.920**	.489**	.656**	.330**	1	-.150	.914**
	Sig. (2-tailed)	.000	.000	.000	.000	.008		.238	.000
Lagging indicator (2015=100)	Pearson correlation	-.420**	-.375**	.380**	.155	-.453**	-.150	1	-.376**
	Sig. (2-tailed)	.001	.002	.002	.221	.000	.238		.002
M0	Pearson correlation	.959**	.998**	.373**	.394**	.189	.914**	-.376**	1
	Sig. (2-tailed)	.000	.000	.002	.001	.135	.000	.002	
M1A	Pearson correlation	.966**	.995**	.383**	.421**	.180	.920**	-.353**	.998**
	Sig. (2-tailed)	.000	.000	.002	.001	.155	.000	.004	.000
M1	Pearson correlation	.967**	.993**	.363**	.416**	.195	.907**	-.367**	.995**
	Sig. (2-tailed)	.000	.000	.003	.001	.122	.000	.003	.000
M2	Pearson correlation	.942**	.995**	.424**	.402**	.168	.924**	-.303*	.994**
	Sig. (2-tailed)	.000	.000	.000	.001	.185	.000	.015	.000
Total monetary M3 deposits	Pearson correlation	.928**	.994**	.435**	.393**	.175	.927**	-.298*	.991**
	Sig. (2-tailed)	.000	.000	.000	.001	.166	.000	.017	.000
Interest rates	Pearson correlation	.497**	.583**	.039	.245	.309*	.505**	-.478**	.584**
	Sig. (2-tailed)	.000	.000	.758	.051	.013	.000	.000	.000
Price of gold per ounce Rand	Pearson correlation	-.929**	-.976**	-.349**	-.421**	-.259*	-.918**	.410**	-.974**
	Sig. (2-tailed)	.000	.000	.005	.001	.039	.000	.001	.000
Exchange rates	Pearson correlation	.531**	.564**	.075	-.158	.030	.388**	-.404**	.555**

	Sig. (2-tailed)	.000	.000	.554	.212	.817	.002	.001	.000

		M1A	M1	M2	Total monetary M3 deposits	Interest rates	Price of gold per ounce Rand	Exchange rates
FTSE JSE listed property J253	Pearson correlation	.966**	.967**	.942**	.928**	.497**	-.929**	.531**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
GDP R million	Pearson correlation	.995**	.993**	.995**	.994**	.583**	-.976**	.564**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
Percentage CPI	Pearson correlation	.383**	.363**	.424**	.435**	.039	-.349**	.075
	Sig. (2-tailed)	.002	.003	.000	.000	.758	.005	.554
Manufacturing (2015=100)	Pearson correlation	.421**	.416**	.402**	.393**	.245	-.421**	-.158
	Sig. (2-tailed)	.001	.001	.001	.001	.051	.001	.212
Leading indicator (2015=100)	Pearson correlation	.180	.195	.168	.175	.309*	-.259*	.030
	Sig. (2-tailed)	.155	.122	.185	.166	.013	.039	.817
Coincident indicator (2015=100)	Pearson correlation	.920**	.907**	.924**	.927**	.505**	-.918**	.388**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.002
Lagging indicator (2015=100)	Pearson correlation	-.353**	-.367**	-.303*	-.298*	-.478**	.410**	-.404**
	Sig. (2-tailed)	.004	.003	.015	.017	.000	.001	.001
M0	Pearson correlation	.998**	.995**	.994**	.991**	.584**	-.974**	.555**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
M1A	Pearson correlation	1	.997**	.994**	.989**	.567**	-.973**	.543**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000
M1	Pearson correlation	.997**	1	.992**	.987**	.560**	-.965**	.545**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
M2	Pearson correlation	.994**	.992**	1	.998**	.532**	-.966**	.562**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000
Total monetary M3 deposits	Pearson correlation	.989**	.987**	.998**	1	.532**	-.966**	.571**

		M1A	M1	M2	Total monetary M3 deposits	Interest rates	Price of gold per ounce Rand	Exchange rates
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000
Interest rates	Pearson correlation	.567**	.560**	.532**	.532**	1	-.561**	-.019
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.880
Price of gold per ounce Rand	Pearson correlation	-.973**	-.965**	-.966**	-.966**	-.561**	1	-.626**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000
Exchange rates	Pearson correlation	.543**	.545**	.562**	.571**	-.019	-.626**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.880	.000	

Table 5.2 shows some degree of collinearity between the money supply variables M0, M1, M1A, M2, M3, the coincident indicator and GDP. However, they all indicate a level of significance > 0.05 except for the leading indicator which had no significant relationship with most of the other independent variables. Most of the variables with collinearity have a significant impact on the output J253 listed real estate pricing variable, hence they cannot be excluded randomly. The binary logistic modelling process solves the problems of collinearity by excluding variables that do not contribute significantly to the model derived as seen in **Error! Reference source not found.** to **Error! Reference source not found.**. The leading indicator series also indicates a relatively high collinearity with other independent variables which implies that the variance it adds to the dependent variable might not be significant.

5.3. Economic indicators for modelling and forecasting of commercial real estate rents in Nigeria

The test for correlation was also conducted on Nigerian data. All the independent variables proved statistically significant at the 0.05 level, except the lending or interest rate which had a P-value of .064. The interest rate also had a low negative correlation of -.281 with the dependent variable. This implies that the regime of the lending rate over the years had a negative correlation and an insignificant impact on the listed real estate market. This result aligns with the findings of Olanrele, Said, Daud and Ab (2015) that REITs are sensitive to interest rates, but with insignificant effect.

Table 5.3 Correlation coefficient of Nigerian variables relative to NSE-listed RE Index

		NSE Listed RE Index	Total GDP	Prime lending/Interest rate (%)	T-bill %	Total money asset	Money supply (M1)	Currency in circulation	Money supply (M2)
NSE Listed RE Index	**Pearson correlation**	1	.372*	-.281	.429**	.385**	.385**	.356*	.375*
	Sig. (2-tailed)		.025	.064	.004	.010	.010	.018	.012

In **Table 5.3**, total GDP shows a low positive correlation with the listed N-REIT index which indicates that a large increase in GDP would lead to growth in the listed real estate pricing. The GDP also indicates a significant relationship with the listed real estate index at 0.025 > 0.05. The Treasury bill (T-bill) rate shows the highest significance at .004 > 0.05. T-bill has demonstrated a moderate positive correlation of 0.429 with the listed real estate sector. This indicates that increases or decreases in Treasury Bill rates would cause increases in listed real estate or N-REIT share prices. This indicates that an increasing treasury bill rate would have growth value for the real estate market in Nigeria.

The prime lending rate or interest rate has a low negative correlation of -0.281 but unlike the case in South Africa, it proves insignificant to the dependent variable. Again, as in South Africa, money supply variables including total money asset, money supply (M1), currency in circulation and money supply (M2) all have a positively significant correlation with the listed real estate market, that is, 0.385, 0.385, 0.356 and 0.375 respectively. This implies that increased money supply, monetary policies and cash in circulation have a significantly positive effect on listed real estate share prices. This agrees with the correlation results of the South African economic indicators in **Table 5.1**.

Table 5.4 Test for multicollinearity across Nigerian independent variables data sets

		Total GDP	Composite Consumer Price Index (%)	Prime lending rate (%)	T-bill %	Total money asset	Money supply (M1)	Currency in circulation	Money supply (M2)
Total GDP	Pearson correlation	1	.168	.020	.462**	.977**	.947**	.934**	.967**
	Sig. (2-tailed)		.275	.899	.002	.000	.000	.000	.000
Composite Consumer Price Index (%)	Pearson correlation	.168	1	.297	.025	.223	.355*	.179	.205
	Sig. (2-tailed)	.275		.050	.872	.146	.018	.245	.182
Prime lending/interest rate (%)	Pearson correlation	.020	.297	1	-.314*	.071	.064	.008	.055
	Sig. (2-tailed)	.899	.050		.038	.648	.681	.957	.723
T-bill %	Pearson correlation	.462**	.025	-.314*	1	.488**	.490**	.541**	.456**
	Sig. (2-tailed)	.002	.872	.038		.001	.001	.000	.002
Total money asset	Pearson correlation	.977**	.223	.071	.488**	1	.973**	.965**	.991**
	Sig. (2-tailed)	.000	.146	.648	.001		.000	.000	.000
Money supply (M1)	Pearson correlation	.947**	.355*	.064	.490**	.973**	1	.953**	.970**
	Sig. (2-tailed)	.000	.018	.681	.001	.000		.000	.000
Currency in circulation	Pearson correlation	.934**	.179	.008	.541**	.965**	.953**	1	.967**
	Sig. (2-tailed)	.000	.245	.957	.000	.000	.000		.000
Money supply (M2)	Pearson correlation	.967**	.205	.055	.456**	.991**	.970**	.967**	1
	Sig. (2-tailed)	.000	.182	.723	.002	.000	.000	.000	

The high multicollinearity noticed between the GDP and money supply (MI), currency in circulation, total money asset and money supply (M2) in **Table 5.4**, confirms the observation in South Africa's selected economic variables also applies to Nigeria. By inspecting the bivariate correlation between the variables, we can see correlation figures against GDP above 0.9. Total Money Asset has a 0. 977 correlation estimates, 0.947 for M1, 0.934 for Currency in Circulation and 0.967 for M2. While in **Table 5.2**, we can see correlation figures > 0.9 between several variables and the GDP. 0.920 for the Coincident Indicator, M0 = 0.998, M1A = 0.995, M1 = 0.993, M2 = 0.995, and M3 = 0.994. This collinearity implies that not all economic variables contribute significantly to modelling the listed real estate market. The models developed must be carefully interpreted when GDP and money market variables are included, as these variables might contain similar information. The logit regression model resolves the multicollinearity by eliminating economic variables that do not explain much of the variation in the listed real estate data series. The high level of significance demonstrated by each of these variables in **Table 5.4** suggests, however, that there might be much variation in the dependent variable NSE Listed RE Index that is explained by these variables.

5.4. Performance of predictive models in identifying market indicators for the Nigerian and South African real estate markets

This study modelled the relationships between macroeconomic variables and listed real estate, using logistic regression. The rationale for this is that logistic regression does not make many of the key assumptions of linear regression and general linear models, and hence the data do not have to be normally distributed or tested for linearity.

A pooled logistic regression model in Table 5.6 with all fourteen selected South African leading indicators was compared to the effect of selectively, excluding variables with insignificant p-values from the model. A multivariate Logit regression is performed in order to evaluate the perfect combination of independent variables for predicting the probability of a decline or rise.

Table 5.5 Omnibus test of Logit Regression Model for all selected South African variables

	Chi-square	**Df**	**Sig.**
Step	23.579	14	.051
Block	23.579	14	.051
Model	23.579	14	.051

The model in **Table 5.5** includes the leading indicator series which showed no statistical significance with the FTSE/JSE J253 Index. The omnibus test of significance shows a P-value > 0.50 which indicates no significance for the model.

Table 5.6 Classification table of Logit Regression Null Model for all selected South African variables

<table>
<tr><th colspan="2" rowspan="3">Observed</th><th colspan="3">Predicted</th></tr>
<tr><th colspan="2">SALRE</th><th rowspan="2">Percentage correct</th></tr>
<tr><th>0</th><th>1</th></tr>
<tr><td rowspan="2">SALRE</td><td>0</td><td>0</td><td>19</td><td>0</td></tr>
<tr><td>1</td><td>0</td><td>45</td><td>100</td></tr>
<tr><td colspan="2">Overall percentage</td><td></td><td></td><td>70.3</td></tr>
</table>

The null model with only the intercept and the dichotomous dependent variable in **Table 5.6** shows that the model explains 70.3% of the variance in the dependent model. The model classifies probabilities of recession (T=0) with a 0% accuracy while it classifies a probability of a recession (T=1) with a 100% accuracy. This implies that a model excluding all macroeconomic variables performs well in predicting growths but is incapable of predicting recessions in the listed real estate market. This also suggests that modelling the contribution of macroeconomic variables might give insight for predicting fall at the expense of higher accuracy in predicting a growth.

Table 5.7 Classification table of Logit Regression Model for all selected South African variables

Observed		**Predicted**		
		SALRE		**Percentage correct**
		0	1	
SALRE	0	10	9	52.6
	1	6	39	86.7
Overall percentage				76.6

The current model slightly outperforms the null model, as seen in Table 5.7 This model, which includes all preliminary selected macroeconomic variables, improved on the null model by 6.3% from 76.6%. - 70.3% = 6.3%

Table 5.8 Pseudo-R values of Logit Regression Model for all selected South African variables

-2 Log likelihood	**Cox & Snell R Square**	**Nagelkerke R Square**
54.305[a]	.308	.437

Table 5.9 Hosmer and Lemeshow goodness of fit test of Logit Regression Model for all selected South African variables

Hosmer and Lemeshow test		
Chi-square	Df	Sig.
3.835	8	.872

The Nagelkerke R-square score in Table 5.8 was 0.437, which indicates a 43.7% explanatory power. In **Table 5.9**, the test for goodness of fit as evidenced in the Hosmer and Lemeshow results reflect a high P-value of 0.872. This result suggests that the model resulting from the interactions between macroeconomic indicators and the listed real estate market fits the data. There is low risk of the model misclassifying or predicting the outcome variable. Despite being substantially fitted, this model's omnibus test shows it proved insignificant at p-value of 0.51. This indicates inclusion of variables of which the input to the variation in the model provides inconsistent responses in the dependent variable.

The indicators were then grouped into two sections, while excluding the leading indicator series which was found to be insignificant in the test for correlation. The groups are divided by the level of correlation with the dependent variable. These groups are:

1. Indicators with a weak or medium negative or positive correlation with the FTSE/JSE J253 indicator ($r \leq 0.05$), excluding the leading indicator series (Model 1). These include interest rates, lagging indicator (2015=100), manufacturing (2015=100), Percentage CPI.
2. Indicators with a strong negative or positive correlation with the FTSE/JSE J253 indicator ($r \geq 0.05$), excluding the leading indicator series (Model 2). GDP (R million), coincident indicator (2015=100), M0, M1A, M1, M2, total monetary (M3) deposits, price of gold per ounce (in rand), exchange rates, constant.

Table 5.10 Omnibus test of Logit Regression Model for indicators with a weak negative or positive correlation with the FTSE/JSE J253 indicator ($r \geq 0.05$)

Chi-square	**Df**	**Sig.**
1.808	4	.771
1.808	4	.771
1.808	4	.771

Table 5.11 Classification table of Logit Regression Model for indicators with a weak negative or positive correlation with the FTSE/JSE J253 indicator ($r \geq 0.05$)

Observed		**Predicted**		
		SALRE		**Percentage correct**
		0	1	
SALRE	0	2	17	10.5
	1	0	45	100.0
Overall percentage				73.4

Table 5.12 Pseudo-R values of Logit Regression Model for indicators with a weak negative or positive correlation with the FTSE/JSE J253 indicator ($r \geq 0.05$)

-2 Log likelihood	**Cox & Snell R-square**	**Nagelkerke R-square**
76.041[a]	.028	.040

Table 5.13 Hosmer and Lemeshow goodness of fit test of Logit Regression Model for indicators with a weak negative or positive correlation with the FTSE/JSE J253 indicator ($r \geq 0.5$)

Chi-square	**Df**	**Sig.**
5.458	8	.708

Model 1 in **Table 5.10** to **Table 5.13** failed the omnibus test of model coefficient with a P-value of 0.771 > 0.05. The omnibus test of significance shows a chi-square value > 0.50 which indicates no significance for the model. The null model with only the intercept and the dichotomous dependent variable in **Table 5.6** shows that the null model explains 70.3% of the variance in the dependent model. The current model slightly outperforms the null model as seen in **Table 5.11**. The model that includes all preliminary selected macroeconomic variables improved on the null model by 3.1% from 70.3 - 73.4%.

The model was able to correctly classify the position of the SALRE at a 73.4% rate. This is a 3.1% improvement on the null model. The Nagelkerke R-square score was 0.040, which indicates a 4% explanatory power. This implies that the model explains only 4% of the variation in the listed real estate series.

Table 5.14 Omnibus test of Logit Regression Model for indicators with a strong negative or positive correlation with the FTSE/JSE J253 indicator ($r \leq 0.05$)

	Chi-square	**df**	**Sig.**
Step	18.928	9	.026
Block	18.928	9	.026
Model	18.928	9	.026

Table 5.15. Classification Table of Logit Regression Model for indicators with a strong negative or positive correlation with the FTSE/JSE J253 indicator ($r \leq 0.05$)

Observed		**Predicted**		
		SALRE		**Percentage correct**
		0	1	
SALRE	0	9	10	47.4
	1	3	42	93.3
Overall Percentage				79.7

Table 5.16 Pseudo-R values of Logit Regression Model for indicators with a strong negative or positive correlation with the FTSE/JSE J253 indicator ($r \leq 0.05$)

-2 Log likelihood	**Cox & Snell R Square**	**Nagelkerke R Square**
58.920[a]	.256	.364

Table 5.17 Hosmer and Lemeshow goodness of fit test of Logit Regression Model for indicators with a strong negative or positive correlation with the FTSE/JSE J253 indicator ($r \leq 0.05$)

Chi-square	Df	Sig.
5.010	8	.757

Table 5.18 Indicators included in the accepted model for South Africa

	B	S.E.	Wald	df	Sig.
GDP at market prices (R million)	.000	.000	.215	1	.643
Coincident indicator (2015=100)	.479	.156	9.467	1	.002
M0	.000	.000	1.509	1	.219
M1A	.000	.000	.403	1	.526
M1	.000	.000	1.135	1	.287
M2	.000	.000	.523	1	.469
Total monetary (M3) deposits	.000	.000	.169	1	.681
Price of gold per ounce (Rand)	.000	.000	3.409	1	.065
Exchange rates	.083	.032	6.598	1	.010
Constant	-74.738	28.311	6.969	1	.008

Model 2 in Table 5.14 **to**

Table 5.18 was significant at the 0.05 level with the omnibus p-value of 0.026. The Hosmer and Lemeshow test show a high value of 0.757, which proves the goodness of fit of the model. A high Hosmer & Lemeshow value is acceptable as an indication of goodness of fit. A low Chi-squared value (with larger p-value closer to 1) indicate a good logistic regression model fit. There is low risk of the model misclassifying or predicting the outcome variable. The Cox & Snell and Nagelkerke R- squared were 0.256 and 0.364 respectively, which implies that the model explains about 25.6% or 36.4% variation in the dependent variables. The model has a 93.3% accuracy in predicting growth (Y=1) while it has a 47.4% accuracy in predicting a decline (Y=0). This model correctly classifies the dependent variable 79.7% and improves on the null model by 9.4%.

Table 5.19 Classification table of Logit Regression Null Model for all Selected Nigerian variables

Observed		**Predicted**		
		NLRE		**Percentage correct**
		0	1	
NLRE	0	0	17	.0
	1	0	19	100.0
Overall percentage				52.8

Table 5.20 Omnibus test of Logit Regression Model for Nigerian indicators

		Chi-square	**Df**	**Sig.**
	Step	20.875	8	.007
	Block	20.875	8	.007
	Model	20.875	8	.007

Table 5.21 Classification table for the full model including all Nigerian indicators

Observed		**Predicted**		
		NLRE		**Percentage correct**
		0	1	
NLRE	0	12	5	70.6
	1	4	15	78.9
Overall percentage				75.0

Table 5.22 Pseudo-R values for the full model including all Nigerian indicators

-2 Log likelihood	**Cox & Snell R-square**	**Nagelkerke R-square**
28.920	.440	.587

Table 5.23 Hosmer and Lemeshow goodness of fit test for the full model including all Nigerian indicators

Chi-square	**Df**	**Sig.**
3.599	7	.825

The logistic regression results of the Nigerian data as seen in **Table 5.20**, show the Omnibus test of model significance less than 0.01 and a Chi-square value of 20.875. This confirms the significance of the independent variables to the model. The Cox & Snell and Nagelkerke R-Square values were .440 and .587 respectively. This translates to 44% and 58.7% estimates of how much of the variation in listed real estate is explained by the model.

Table 5.24 Indicators included in the accepted model for Nigeria

	B	S.E.	Wald	Df	Sig.
Total GDP	.000	.000	4.419	1	.036
Composite Consumer Price Index (%)	-.034	.086	.153	1	.695
Prime lending/interest rate (%)	.143	.331	.187	1	.666
T-bill %	-.037	.064	.339	1	.560
Total money asset	.000	.000	4.087	1	.043
Money supply (M1)	.000	.000	.198	1	.656
Currency in circulation	.000	.000	2.307	1	.129
Money supply (M2)	.000	.000	6.249	1	.012
Constant	-21.938	21.429	1.048	1	.306

The model for Nigeria in

Table 5.19 - Table 5.24 was significant at the 0.01 level with the omnibus p-value of 0.007>0.01. The Hosmer & Lemeshow test shows a value of 0.825 which proves the goodness of fit of the model. A high Hosmer & Lemeshow value is acceptable as an indication of goodness of fit small Chi-squared values (with larger p-value closer to 1) indicate a good logistic regression model fit. This indicates that the model fits the data used. There is low risk of the model misclassifying or predicting the outcome variable. The Cox & Snell and Nagelkerke R-squared were 0.440 and 0.587 respectively, which implies that the model explains about 44.0% or 58.7% variation in the dependent variables. The model has a 78.9% accuracy in predicting growth (Y=1) while it has a 70.6% accuracy in predicting a decline (Y=0). The cumulative predictive accuracy on the classification table is 75%, which is a 22.2% increase from 52.8% recorded in the null model with only the intercept in the model.

5.5. Development of forecasting models for early detection of turning points in commercial real estate rental values in Nigeria and South Africa

The results of the correlation show the significant relationship between most of the selected economic variables and the listed real estate variable. The influence of these variables on the dichotomous independent variable is presented in a regression analysis.

T; being the state of the independent variable is estimated to be 1 or 0, based on the logit regression rule:

T = 1 for the period that capital values decline

T = 0 otherwise

Therefore, the objective of using a logit approach is to estimate a response probability:

$Pr\ (T = 1|x) = Pr\ (T = 1|\ x1, x2, ..., xk)$

$Pr\ (T = 1|x) = \log(p/1\text{-}p) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k$

The logit model provides the best fitted combination of macroeconomic variables that improves on the null/naïve model. The probabilities are summed up or down between 0 and 1 to provide the forecast based on thresholds like 0.5, 0.7, 0.9. These thresholds are arbitrary and thus require the analyst understanding of the market's sensitivity to changes in these economic variables.

The β (beta coefficient) values for South African data sets showed the coincident indicators and exchange rates with significance score on the 0.01 level. **Error! Reference source not found.** shows that 9.4% variance in South African real estate is explained by changes in the exchange rate and coincident indicators. Both the exchange rate and coincident indicator show a positive influence on the listed real estate indicator. This signifies that an increase in these two economic indicators will impact positively towards a growth in the listed real estate market. In Equation 5.1, the coincident indicator β = 0.479 and the Exchange rate β = 0.083. The constant or intercept value was -74.738.

This model is expressed thus:

$Y = \log(p/1\text{-}p) = \beta 0 + \beta 1CI + \beta 2ER$

$Y = Pr\ (T = 1|x) = \log(p/1\text{-}p)$ or *ln* (ODDS) = + 0.479 (CI) + 0.083 (ER) **Equation 5.1**

Where:

Y = SALRE

Pr = Probability

β_0 = Model intercept

β_x= Regression coefficient

CI = Coincident Indicator

ER = Exchange Rate

For the Nigerian data sets, the β (beta coefficient) values showed the lending rate, treasury bill rate and consumer price index/inflation, with significance score on the 0.01 level. **Table 5.24 Indicators included in the accepted model for Nigeria** shows that 22.2% variance in the market is explained by changes in the interest rate, Treasury Bill rate and the composite consumer price (inflation). Only the interest rate shares a positive relationship with the independent variable in **log(p/1-p) or *ln* (ODDS) = -21.938 + 0.143(IR) - 0.037 (TBR) - 0.034 (CPI)** Equation 5.2. The Treasury Bill rate and inflation rate indicate a negative relationship with the listed real estate market indicator. This signifies that an increase in the Treasury Bill rate and inflation rate will impact negatively towards a decline in the listed real estate market. The coefficient for variables in the equation is summarised in the logit regression equation as:

Y = Pr (T = 1|x) = log(p/1-p) or *ln* (ODDS)

log(p/1-p) or *ln* (ODDS) = -21.938 + 0.143(IR) - 0.037 (TBR) - 0.034 (CPI) **Equation 5.2**

Where:

Y = NLRE

Pr = Probability

IR = Lending/interest rate

TBR = Treasury Bill rate

CPI = Consumer Price Index

5.6. Comparison of model performance in identifying leading economic indicators in Nigeria and South Africa

In comparing the logit models, the two common approaches used are the following:

1. The model misclassification rate;
2. The ROC curves.

Table 5.25. The Model Misclassification rate

Country	Classification accuracy of fitted model (%)	Improvement on null model (%)	Misclassification rate
South Africa	79.7	9.4%	20%
Nigeria	75.0	22.2%	25%

The Nigerian logit model outperforms the South African logit model by a 22.2% improvement on the null model as against the 9.4% improvement observed in the South African model. However, the misclassification rate for the Nigerian logistic model is 5% higher. The classification accuracy of the South African logit model is higher than that of the Nigerian logit model. This suggests that while 22% variation in Nigerian listed real estate market is explained by macroeconomic indicators; and 9.4% variation is explained in the South African market, the South African model includes indicators that are more reliable in accurately predicting the real estate market.

The time series data available for Nigeria were limited to ten years, while that of South Africa was fifteen years. This could also be the reason for the higher level of classification accuracy for the South African Logit model.

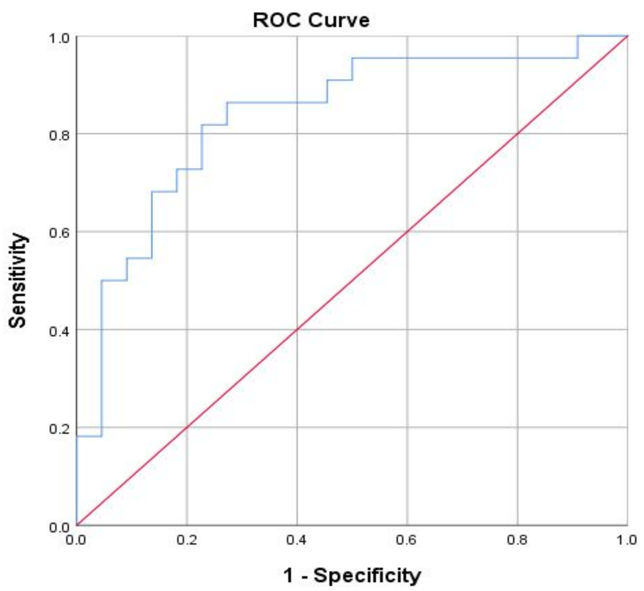

Figure 5.1 ROC curve for Nigerian predicted probabilities

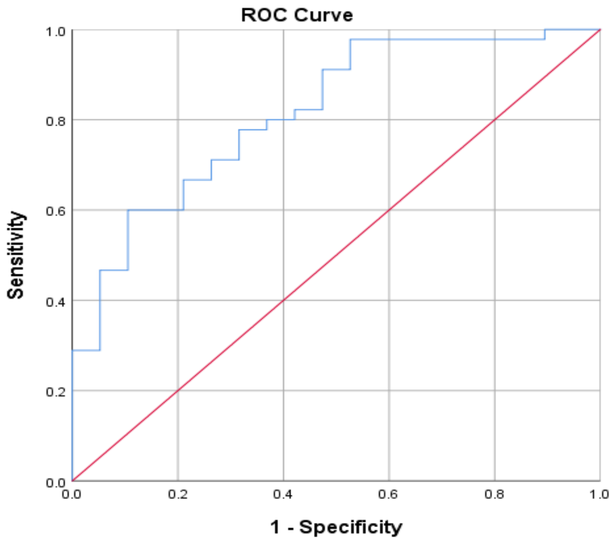

Figure 5.2 ROC Curve for South African predicted probabilities

Table 5.26. Area Under the Curve for South Africa Predicted Probabilities

Area	**Std. Error**[a]	**Asymptotic Sig.**[b]	**Asymptotic 95% confidence interval**	
			Lower bound	**Upper bound**
.815	.057	.000	.704	.927

Table 5.27. Area Under the Curve for Nigeria Predicted Probabilities

Area	**Std. Error**[a]	**Asymptotic Sig.**[b]	**Asymptotic 95% confidence interval**	
			Lower bound	**Upper bound**
.837	.062	.000	.714	.959

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

The area under the curve for Nigeria is 0.837, with 95% confidence interval (.714, .959). The area under the curve is also significantly different from 0.5 since p-value is .000. Similarly, for South Africa, the area under the curve is 0.815, with 95% confidence interval (.704, .927). The area under the curve is also significantly different from 0.5, since the p-value is .000. In the two models, the logistic regression classifies the group significantly better than by chance. The classification similarities between the two models from South African and Nigerian data are visualised in **Figure 5.1Error! Reference source not found.Figure 5.2**.

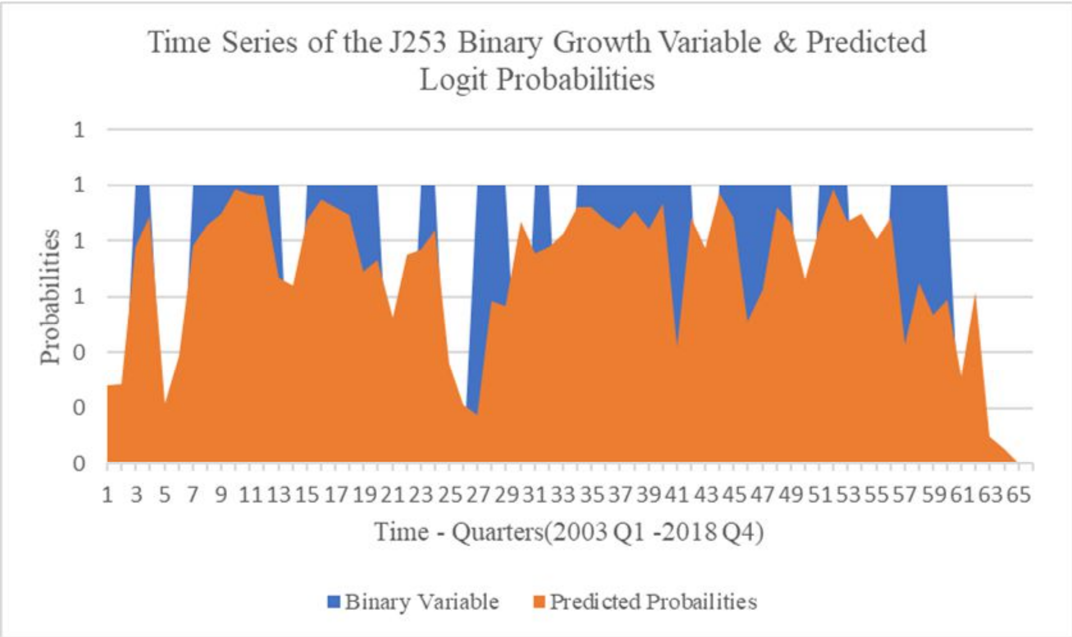

Figure 5.3 Time series of the J253 Binary Growth Variable and Predicted Logit Probabilities

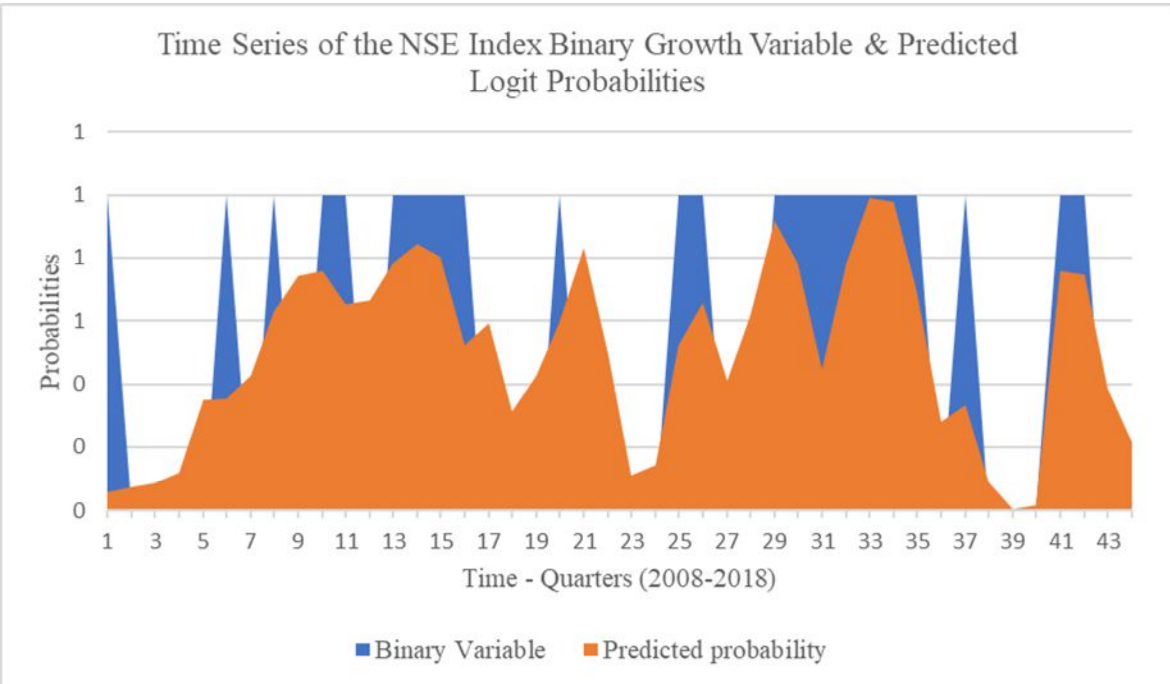

Figure 5.4 Time series of the NSE Binary Growth Variable and Predicted Logit probabilities

In **Figure 5.3** and **Figure 5.4** the time series of the dependent variable is plotted against the probabilities predicted by the Logit model in each model. Comparing the probabilities predicted by each model with the actual peak or trough in the data collected, creates a visual aid for comparing the performance of the models derived.

These forecasting visualisation reports the in-sample forecasting results. The predicted probabilities for the South African model as seen in **Error! Reference source not found.** reach a peak, while frequently coinciding with the J253 growth. The declines in the data coincide only twice in Q4 of 2003 and 2008, however. The South African model may predict probabilities of growth more accurately than it predicts falls.

Conversely, the probabilitites of the Nigerian model coincide almost as accurately in the declines as they do in the peaks. This can be seen in **Error! Reference source not found.**. The Nigerian market demonstrates a more responsive listed real estate market to economic indicators and thus allows for a greater degree of forecasting to be achieved when considering the relationship between economic data and the listed real estate market.

5.7. Chapter summary

This section compares data from Nigerian and South African listed real estate markets using the FTSE/JSE J253 and the weighted average of the Skye REIT and UACN property development company for Nigeria. The South African macroeconomic and listed real estate time series data spanned fifteen years, while for Nigeria it spanned ten years. The results of the data analysis show that reliable indicators were identified for modelling the listed commercial real estate data in Nigeria and South Africa. The two economies respond to different macroeconomic variables. However, the performance of the variables proves that the logit model significantly forecasts the future rent movements.

The study shows that emerging listed real estate data and forecasting in South Africa and Nigeria responded differently to macroeconomic variables. This aligns with the findings of Olanrele, Said and Daud (2015) in their comparison of Malaysian and Nigerian REITs. They posited that differences in REIT structure and features could be determining factor(s) in investment performance. However, the positive relationship between interest rate and the Nigerian listed real estate index counters the position of Olanrele, Said and Daud (2015) who suggested that a more accessible interest rate would boost performance and growth. This might be because commercial real estate prices hedge against inflation and rising costs.

The Nigerian logistic model that was derived, confirmed similar findings as those of Olanrele *et al.* (2019), who held that only three indicators, being the primary lending rate (PLR), corporate private sector (CPS) and the Treasury Bill rate (TBR) have a significant effect on REIT yields, but in different directions. For the listed real estate, the difference in the model is the Consumer Price Index which replaces CPS as the third indicator besides PLR and TBR. This study goes further than that, by including variables outside monetary market indicators as employed in Olanrele et al (2019).

CHAPTER 6.

CONCLUSION AND RECOMMENDATIONS FOR FUTURE REVIEW

6.0. Introduction

This research sought to investigate predictive modelling of rent in South Africa and Nigeria. The use of logistic regression was by means of this study introduced as an improvement to overcome the limitations of traditional real estate pricing, especially the scarcity of comparative data. Introducing macroeconomic indicators as predictors of listed real estate markets subsequently proved to be a valuable approach for detecting turning points.

A major role of the investment analyst is to mitigate risk and uncertainty. This research confirmed the validity of logit models as an improved approach for detecting the probability of imminent changes in the commercial listed real estate market. This modelling approach serves as a means to overcome the scarcity of direct property data by considering the data in financial reports of listed real estate companies in Nigeria and South Africa.

6.1. Realisation of study objectives

The study was carried out to answer the main research question - What are the most reliable economic indicators for rental forecast in the Nigerian and South African real estate markets? This was further divided into the following sub-questions:

- What leading economic indicators exist for modelling and forecasting of commercial real estate rent?
- How well do existing predictive models perform relative to identified economic indicators?

- Can a relationship be established for early detection of turning points in commercial real estate rental values?
- How well do the predictive models perform with leading economic data from South Africa, as compared to Nigeria?

The succeeding paragraphs in this section answers the aforementioned questions. This also provides insight into the outcome or realisation of the purpose of this research work.

6.1.1. A rigorous literature research provided information relative to identifying the common leading economic indicators for modelling and forecasting of commercial real estate rents. These indicators were tested for their relationship with indicators of listed commercial real estate in South Africa and Nigeria. The South African macroeconomic variables that were evaluated, included the GDP at market prices (R million), Percentage CPI Consumer prices: CPI, excluding food and non-alcoholic beverages and fuel (all urban areas), manufacturing (2015=100), leading indicator (2015=100), coincident indicator (2015=100), lagging indicator (2015=100), M0, M1A, M1, M2, total monetary (M3) deposits, exchange, interest rates and the gold price. Nigerian macroeconomic variables included the total GDP, prime lending/interest rate (%), the Treasury Bill Rate (%), the total money asset, money supply (M1), currency in circulation, and money supply (M2).

6.1.2. The logistic regression model evaluated the performance of the best fitting model to classify the state of a dummy variable T = 1 or 0 representing growth or decline in the listed real estate indicators. The test for predictive accuracy showed that 22.2% variance in the Nigerian real estate market was explained by the logit regression model, while

9.4% variance in the South African real estate was explained by changes in the exchange rate and coincident indicators. The strength and similarity of the model capacity in both countries showed that each market signal correctly predicts turning points in the economy for as much as 75% (Nigeria) and 80% (South Africa) of the time.

6.1.3. The models derived from the logit regression model express the relationship that the macroeconomic variables share with the listed real estate market in the detection of turning points. Both the exchange and coincident indicator show a positive influence on the South African listed real estate indicator. On the other hand, only the interest rate shares a positive relationship with the Nigerian market. The Treasury Bill Rate and inflation rate indicate a negative relationship with the Nigerian listed real estate market indicator. The modes take the form: $Y = \log(p/1\text{-}p) = \beta 0 + \beta_1 X_1 + \ldots, + \beta x Xx$.

6.1.4. In comparing relative performance, the misclassification table and ROC curve prove insight into the relative performance of the two models. The Nigerian logit model outperforms the South African logit model by a 22.2% improvement on the null model as against the 9.4% improvement observed in the South African model. The misclassification rate for the Nigerian logistic model is however 5% higher. Meanwhile, the classification accuracy of the South African logit model is higher than that of the Nigerian logit model. The two models of the logistic regression function classify future direction of listed real estate markets in South Africa and Nigeria significantly better than by chance.

6.2. Conclusion

This study investigated the use of the logit regression framework for predictive rent modelling in the Nigerian and South African real estate markets. The use of this macroeconomic modelling approach for predicting the future trajectory of rent proved to be useful for anticipating turning points in the real estate market. This also serves the purpose of early warning signals for decision-makers about impending changes in the general economy which might affect real estate investment. This modelling process using the logit regression model allows the analyst to predict signals in the indirect real estate market with up to 80% accuracy. This potentially reduces the risk and uncertainty associated with participation in the real estate markets of emerging African economies like Nigeria and South Africa.

The major weakness of these models is that they rely significantly on macroeconomic time series that might not be available for similar periods. The periodicity of several data sources is annual and they do not provide a large enough data set from which modelling can adequately take place. These indicators are thus excluded from the model and analysis does not account for such macroeconomic effects in the long run.

The study also concluded that not all economic indicators lead the listed real estate market. The combination of some of these significant variables aid in explaining variations in the listed real estate indicator. The best fitted models in South Africa and Nigeria also perform well in classifying the in-sample data. However, some data introduced too much variance to the SA model, resulting in a statistically insignificant model. Excluding the leading indicator from the logit regression model produced a significant model that improved on the null model. Indicators that displayed no significant relationship with the listed real estate indicator might introduce excessive variance to the model, making it unreliable. This could not be tested for several variables, because it was an isolated occurrence with one variable.

Excluding variables with a low level of correlation from the model aided in improving its predictive accuracy. This supports the assumption that a high level of correlation implies existing price discovery and signals in a macroeconomic variable. The research was further able to develop forecasting models for early detection of turning points in commercial real estate rental values in South Africa and Nigeria.

The comparison of the resultant models showed that both models were a significant improvement on rule of thumb and display high levels of accuracy in classifying the state of the listed real estate variable using the ROC curve of predicted probabilities and tables of misclassification rates.

6.3. Recommendations for future research

In Nigeria, the rise of data-driven evaluations has only begun. Nigeria is witnessing the emergence of real estate analysts and organisations like Estate Intel and Roland Igbinoba housing index. As these organisations expand their real estate data collection, it would be important to determine the reliability of such data for investment analysis.

Exploring the applicability of econometric modelling would therefore serve as a good basis for evaluating the data provided by these platforms and what sources of signals should receive attention, especially in the capital market. It is not enough to generate indices or consensus data. It is further important to evaluate the reliability of such data. It is also important to understand the relationship that exists between commercial real estate data and economic data. This provides a reliable basis for forecasts, as demonstrated in this research.

There are limitations to this study, largely including access to data such as the ABSA housing index. Similar databanks such as those found on the MoneyWeb site and other platforms are only accessible on payment. The study was, however, done as accurately as the available data made it possible. This led to some recommendations such as the following:

1. Nigeria and South Africa must encourage listed real estate operations and indices.
2. Further study could be done towards understanding predictive probabilistic models. There is a need to evaluate the accuracy they add to real estate market analysis and reporting.
3. Further research could be conducted on how econometric models should fit into business reporting for residential and commercial real estate companies. This would make it possible to evaluate data on real estate performance, based on consistent data sources such as listed real estate data.
4. Open data policies should be adopted in more economies in order to improve access to data. A bigger array of data sources would provide a more valid basis for quantitative evaluations.
5. Directional forecasting should be explored in depth, as it is more likely to serve towards advising investors than point forecast.
6. Property indexes should be built on their capacity to explain the relationship between the economy and real estate data. Without this, evaluations would hardly be any better than rule of thumb estimates or a flip of the coin.

This research has succeeded in adapting logistic regression as a macroeconomic modelling approach for real estate forecasting in South Africa and Nigeria. The study ultimately shows the possibility of achieving greater real estate forecast accuracy, using macroeconomic data. There is a lot of room for further study into this statistical modelling approach and its applicability to out of sample data forecast.

REFERENCES

Abidoye, R. and Albert, C. (2018) ‘Hedonic Valuation of Real Estate Properties in Nigeria’, *Journal of African Real Estate Research*, 1(1), pp. 122–140.

Abidoye, R. B. and Chan, A. P. C. (2016) ‘A Survey of Property Valuation Approaches in Nigeria’, *Property Management*, 34(5), pp. 364–380.

Akinsomi, O., Mkhabela, N. and Taderera, M. (2018) ‘The Role Of Macro-Economic Indicators In Explaining Direct Commercial Real Estate Returns: Evidence From South Africa’, *Journal of Property Research*. Routledge, 35(1), pp. 28–52.

Anas, J. and Laurent, F. (2003) 'Detecting Cyclical Turning Points', *26th CIRET Conference, Taipei*. Luxembourg: European Commission.

Anas, J. and Laurent, F. (2004) Detecting Cyclical Turning Points, *Journal of Business Cycle Measurement and Analysis*.

Anderson, L. M. and Cordell, H. K. (1988) ‘Influence of Trees on Residential Property Values in Athens, Georgia (U.S.A.): A Survey Based on Actual Sales Prices’, *Landscape and Urban Planning*, 15(1–2), pp. 153–164.

Aron, J. and Muellbauer, J. N. J. (2009) ‘Some Issues in Modeling and Forecasting Inflation in South Africa .’, *Social Research*, pp. 29–31.

Artis, M., Bladen-Hovell, R., Osborn, D., Smith, G. and Zhang, W. (1995) ‘Turning Point Prediction for the UK Using CSO Leading Indicators’, *Oxford Economic Papers*, 47(3), pp. 397–417.

Ashuri, B. and Shahandashti, S. M. (2012) ‘Quantifying the Relationship between Construction Cost Index (CCI) and Macroeconomic Factors in the United States’, in *48th*

ASC Annual International Conference. Associated Schools of Construction. Available at: http://ascpro.ascweb.org/chair/paper/CPRT222002012.pdf.

Ayodele, T. O., Olaleye, A. and Araloyin, F. M. (2016) 'Performance of Listed Property Stock in Mixed Asset Portfolio in Nigeria', *Journal of Environmental Design and Management*, 8(1 & 2), pp. 190 – 207.

Baba, C. and Kisinbay, T. (2011) 'Predicting Recessions: A New Approach for Identifying Leading Indicators and Forecast Combinations'. *IMF Working Paper WP/11/235*.

Barnard, N. and Oranje, M. (2014) 'Proxy Indicators as Measure of Local Economic Dispositions in South Africa : An Exploratory Study', *Town and Regional Planning*, 65, pp. 12–22.

Bello, O. M. and Yacim, A. J. (2014) 'An Assessment of the Impact of Tree Shade on Rental Value of Residential Property in Maiduguri, North – Eastern, Nigeria', in FIG Congress 2014. Kuala Lumpur, Malaysia, pp. 1–18.

Boshoff, D. (2013a) 'Empirical Analysis of Space and Capital Markets in South Africa: A Review Of The REEFM- and FDW Models', *South African Journal of Economic and Management Sciences*, 16(4), pp. 383–394.

Boshoff, D. (2013b) 'Investigation Into the Supply of Information and Measurement of Transparency in The Listed Property Sector', *Acta Structilia*, 20((2)), pp. 30–49.

Boshoff, D. (2013c) Towards a Listed Real-Estate Investment Valuation Model. *University of Pretoria*. Available at: http://repository.up.ac.za/handle/2263/32819.

Boshoff, D. (2013d) 'Towards a Listed Real Estate Investment Alternative Hypothesis', *South African Journal of Economic and Management Sciences*, 16(3), pp. 329–346.

Boshoff, W. H. (2005) 'The Properties of Cycles in South Africa Financial Variables and

Their Relation to The Business Cycle', *South African Journal of Economics*, 73(4), pp. 694–709.

Boshoff, W. H. and Binge, L. H. (2019) 'Business Sentiment and the Business Cycle in South Africa', in *Alternative Cycle Indicators for the South African Business Cycle*, pp. 1–20.

Brooks, C. and Tsolacos, S. (2000) 'Forecasting Models of Retail Rents', *Environment and Planning A*, 32(10), pp. 1825–1839.

Michael, B. and Almeida, P. (2016) *Understanding the Commercial Real Estate Investment Ecosystem. An Early Warning System Prototype*. World Economic Forum REF 080116.

Burns, A. and Wesley, M. (1946) 'The Basic Measures of Cyclical Behavior'. National Bureau of Economic Research. Available at: http://www.nber.org/chapters/c2984.

Camacho, M. and Perez-quiros, G. (2000) 'This is What The Leading Indicators Lead', *Journal of Applied Economics*, 17(1), pp. 61–80.

Chrostek, K. and Kopczewska, K. (2013) 'Spatial Prediction Models for Real Estate Market Analysis', *Ekonomia*, (35), pp. 25–43.

Clark, A. and Daniel, T. (2006) 'Forecasting South African House Prices', *Investment Analysts Journal*, 35(64), pp. 27–33.

Clark, A. E. and Daniel, T. (2006) 'Forecasting South African House Prices', *Investment Analysts Journal*, 35(64), pp. 27–33.

Crosby, N. and Henneberry, J. (2010) 'Changing Investment Valuation Practices in the UK', in *Annual Conference of the European Real Estate Society*, pp. 23–26.

D'Arcy, É., McGough, T. and Tsolacos, S. (1999) 'An Econometric Analysis and Forecasts of The Office Rental Cycle in The Dublin Area', *Journal of Property Research*, 16(4), pp. 309–321.

Emele, C., Umeh, O. and Okpaleke, F. (2019) ‘Commercial Real Estate Market Forecasts: Complexities and Methodologies in the Lagos Mega City’, (1995), pp. 35–38.

Emerole, C. G. (2018) ‘Risks and Opportunities in Emerging Markets International Real Estate Investment: A Comparative Analysis of Nigeria and South Africa’, *Journal of the Nigerian Institution of Estate Surveyors and Valuers*, 41(1), pp. 71–78. Available at: https://www.researchgate.net/publication/327069075.

Frankel, J. and Saravelos, G. (2012) ‘Can Leading Indicators Assess Country Vulnerability? Evidence from The 2008-09 Global Financial Crisis’, *Journal of International Economics*. Elsevier B.V., 87(2), pp. 216–231.

French, N. (2005) ‘Property Investment & Finance’, in *Property Investment Valuation*, pp. 248–304.

Füss, R., Stein, M. and Zietz, J. (2012) ‘A Regime-Switching Approach to Modeling Rental Prices of U.K. Real Estate Sectors’, *Real Estate Economics*, 40(2), pp. 317–350.

Gordon, S. (2016) *Value of all global real estate totals $217 trillion*, *Pam Golding Properties*. Available at: https://www.pamgolding.co.za/property-research/2016/2/2/value-of-all-global-real-estate-totals-217-trillion (Accessed: 21 April 2019).

Guerard, J. B. (2013) ‘Introduction To Financial Forecasting In Investment Analysis’, *Introduction to Financial Forecasting in Investment Analysis*, (2007), pp. 1–236.

Hamilton, J. (1989) ‘A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle’, *Econometrica*, 57(2), pp. 357–384.

Harding, D. and Pagan, A. (2002) ‘A Comparison of Two Business Cycle Dating Methods’, *Journal of Economic Dynamics & Control*, 27, pp. 1681–1690.

Harrami, H. and Paulsson, O. (2017) 'Rent Modelling Of Swedish Office Markets'. Royal

Institute of Technology, Stockholm, Sweden.

Hongkong Shangai Banking Corporation (HSBC) (2017) *Global Real Estate*.

Ibiyemi, A. O. and Adenipekun, M. T. A. (2013a) 'A Study of Errors Arising from Property Investment Income Capitalization Techniques', *Mediterranean Journal of Social Sciences*, 4(6), pp. 639–646.

Ibiyemi, A. O. and Adenipekun, M. T. A. (2013b) 'A Study of Errors Arising from Property Investment Income Capitalization Techniques', 4(6), pp. 639–646.

Iroham, C. O., Oluwunmi, A. O., Simon, R. F. and Akerele, B. A. (2014) 'Assessing the Trend in Rental Values of Commercial Properties Along Oyemekun', *Covenant Journal of Research in the Built Environment (CJRBE)*, 1(1).

Jadevicius, A., Sloan, B. and Brown, A. (2013) 'Examination of Property Forecasting Models - Accuracy and Its Improvement Through Combination Forecasting', *School of Engineering and the Built Environment, Edinburgh Napier University*, p. 20.

Jadevicius, A., Sloan, B. and Brown, A. (2013) 'Property Market Modelling and Forecasting: a Case for Simplicity', in *20th Annual European Real Estate Society Conference*, pp. 3–6. Available at: http://eres.scix.net/data/works/att/eres2013_10.content.pdf.

Karakozova, O. (2005) *Modelling And Forecasting*. Helsinki, Finland Distributor: Edita Prima Ltd, Helsingfors.

Keng, T. Y. (2004) 'Australian Property Securities Funds: A Survey of Strategic Investment Issues', *Pacific Rim Property Research Journal*, 10(3), pp. 263–282.

Krystalogianni, A., Matysiak, G. and Tsolacos, S. (2004) 'Forecasting UK commercial real estate cycle phases with leading indicators: A probit approach', *Applied Economics*, 36(20), pp. 2347–2356.

MacFarlane, J., Murray, J., Parker, D. and Peng, V. (2001) 'Forecasting Property Market Cycles: An Application of the Rics Model to the Sydney Cbd Office Market', in *8th Pacific Rim Real Estate Society Conference Christchurch*. New Zealand: RICS Research Foundation, pp. 1–20.

Monde, M. (2008) 'The Turning of The Cycle and The Impact of Interest Rates', in *4th Convention of the South African Institute of Black Property Practitioners (SAIBPP) at*. Midrand, South Africa: South African Institute of Black Property Practitioners (SAIBPP).

Moolman, E. and Jordaan, J. (2005) 'Can Leading Business Cycle Indicators Predict the Direction of the South African Commercial Share Price Index?', *The South African Journal of Economics*, 73(1), pp. 68–78.

Mourouzi-Sivitanidou, R. (2011) 'Basic Real Estate Economics', *Financing Urban Regeneration - Technical Workshop*. Johannesburg, South Africa: Jones Lang LaSalle (JLL), pp. 30–70. Available at: isites.harvard.edu/fs/docs/icb.topic1143374.../Rena__Chap 2.pdf.

Munusamy, M., Muthuveerappan, C. and Baba, M. (2015) 'An Overview of the Forecasting Methods Used in Real Estate Housing Price', *Jurnal Teknologi*, 5(73), pp. 189–193.

Naidoo, P. (2019) *As African Leaders Meet on Growth, Leading Economies Are a Drag*, *Bloomberg*. Available at: https://www.bloomberg.com/news/articles/2019-09-02/as-african-leaders-meet-on-growth-leading-economies-are-a-drag.

Namnso, U., Ighalo, J. and Sanusi, Y. (2015) 'Modelling the Office Rental Market in Selected Districts of Abuja ', *De Gruyter*, 7(28), pp. 64–72.

Ng, B. F. and Higgins, D. (2007) 'Modelling the commercial property market: An empirical study of the Singapore office market', *Pacific Rim Property Research Journal*, 13(2), pp. 176–193.

Ntuli, M. and Akinsomi, O. (2017) ‘An Overview of The Initial Performance of The South African REIT Market’, *Journal of Real Estate Literature*, 25(2), pp. 365–388.

Olanrele, O. O., Adegunle, T. O., Fateye, O. B. and Ajayi, C. A. (2019) ‘Causal Relationship between N-REIT ’s Dividend Yield and Money Market Indicators’, *Journal of African Real Estate Research*, 4(1), pp. 71–91.

Olanrele, O. O., Said, R. and Daud, N. (2015) ‘Comparison of REIT Dividend Performance in Nigeria and Malaysia’, *African Journal of Business Management*, 9(16), pp. 608–614.

Olanrele, O. O., Said, R., Daud, N. and Ab, R. (2015) ‘N-REIT Performance in the Face of Index Computation and Risk Adjusted Return’, in *21st Annual Pacific-Rim Real Estate Soceity Conference*. Kuala Lumpur, Malaysia.

Olanrele, O. and Said, R. (2014) ‘Real Estate Investment Trusts (REITs) Industry in Nigeria: The Influence of External Factors on Returns.’, in *The 14th African Real Estate Society (AfRES) Annual Conference*. Cape Town, South Africa.

Olawande, O. N. I. A., Emoh, F. I. and Ijasan, K. C. (2012) ‘The Impact Of Money Market Indicators On Real Estate Finance In Nigeria’, *Sri Lanka Journal of Real Estate*, (6), pp. 16–37.

Olowofeso, O., Bada, A., Bamanga, M., Bassey, K. and Dzaan, K. (2008) ‘On the Development of Residential Property’, *CBN Journal of Applied Statistics Vol.3 No.2*, 3(2), pp. 17–38.

Oni, A. O. (2010) ‘Arterial Road Network and Commercial Property Values: Case Study of Ikeja, Nigeria By Oni, Ayotunde Olawande’, in *Business Luncheon/MCPD Organized by RICS Nigeria Group*.

Özyurt, S. (2014) *Spatial dependence in commercial property prices micro evidence from the*

Netherlands. ECB Working Paper 1627. Frankfurt, Germany. Available at: http://ssrn.com/abstract_id=2381860.

Potgieter, J. (2017) *Drivers of change for the Real Estate Industry*, *Pwc*. Available at: www.pwc.co.za.

Rossouw, J. (2016) *South Africa is Africa's largest economy (again). But what does it mean?*, *The Conversation*. Available at: https://theconversation.com/south-africa-is-africas-largest-economy-again-but-what-does-it-mean-63860.

Sibanda, M. (2013) 'The Interaction Between Property Returns And The Macroeconomy: Evidence From South Africa', *International Journal of Business and Social Research*, 3(4), pp. 146–152. Available at: https://thejournalofbusiness.org/index.php/site/article/view/39.

Simo-Kengne, B. D., Balcilar, M., Gupta, R., Reid, M. and Aye, G. C. (2012) *Is The Relationship Between Monetary Policy And House Prices Asymmetric In South Africa? Evidence From A Markov-Switching Vector Autoregressive Model*. Stellenbosch Economic Working Papers: 15-26. Matieland, South Africa. Available at: https://ideas.repec.org/p/pre/wpaper/201222.html.

Standish, B., Lowther, B., Morgan-Grenville, R. and Quick, C. (2005) 'The Determinants of Residential House Prices in South Africa', *Investment Analysts Journal*, 3523(61), pp. 41–48.

Tonelli, M. and Cowley, M. (2004) 'Forecasting Office Building Rental Growth Using a Dynamic Approach', *Pacific Rim Property Research Journal*, 10(3), pp. 283–304.

Tsolacos, S. (2006) 'An Assessment of Property Performance Forecasts: Consensus Versus Econometric', *Journal of Property Investment & Finance*, 24(5), pp. 386–399.

Tsolacos, S. (2012) 'The Role of Sentiment Indicators For Real Estate Market Forecasting', *Journal of European Real Estate Research*, 5(2), pp. 109–120.

Tsolacos, S. and Brooks, C. (2010) *Real Estate Modelling & Forecasting*. New York, United States of America: Cambridge University Press.

Tsolacos, S., Brooks, C. and Nneji, O. (2014) 'On the Predictive Content of Leading Indicators: The Case of U.S. Real Estate Markets', *American Real Estate Soceity*, 36(4), pp. 541–573.

Tsolacos, S., Chris, B. and Ogonna, N. (2014) 'On the Predictive Content of Leading Indicators : The Case of U . S . Real Estate Markets', *J R E R*, 36.

Udobi, N., Kalu, U. and Elekwachi, M. (2016) 'Challenges of International Real Estate Investment in an Emerging Economy: The Nigerian Experience', 8(3), pp. 90–97. Available at: www.iiste.org.

Udoekanem, N. B. and Ighalo, J. I. (2015) 'Office Rental Determinants in WUSE Commercial District of Abuja, Nigeria', *University of Mauritius Research Journal*, 21, pp. 2001–2012. Available at: http://www.ajol.info/index.php/umrj/article/view/122073.

Udoekanem, N., Ighalo, J. and Sanusi, Y. (2015) 'Predictive Modeling of Office Rent in Selected Districts of Abuja, Nigeria', *De Gruyter*, 23(4), pp. 95–104.

Viezer, T. W. (1999) 'Econometric Integration of Real Estate ' s Space and Capital Markets', *Journal Of Real Estate Research*, 18(3), pp. 503–519.

Van Der Walt, B. E. and Pretorius, W. S. (2004) 'Notes on Revision of the Composite Business Cycle Indicators', *South African Reserve Bank*, pp. 29–35.

Yunus, N. (2012) 'Modeling Relationships among Securitized Property Markets , Stock Markets and Macroeconomic Variables', *Journal of Real Estate Research, American Real Estate Society,* 34(2), pp. 127-156.