A Comparative Approach to Market Wide Herding

by

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Declaration

I declare that this Ph.D. Thesis is my own, unaided work. It is submitted in partial fulfilment of the degree of Doctor of Philosophy in the subject area of Finance at the University of the Witwatersrand, Johannesburg, South Africa. It has not been submitted before for any degree or examination in any other university.

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Preface

Parts of this thesis have been accepted or submitted for publication as follows:

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Dedication

I dedicate this work firstly to God my saviour, strength and protector. I also dedicate this work to my parents Maggie Zwane and my late father Thulani Hector Zwane, my sister Thembi Zwane and my beautiful little girl Khanya Langalethu Zwane.

Lastly, to my grandmother Nostah Sedibe who never got the opportunity to get the education she so yearned for. You instilled and preached the importance of education to all your children and grandchildren, thank you KOKWANE!

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List of Abbreviations

CSAD Cross-Sectional Absolute Dispersion (2000) model
CSSD Cross-Sectional Standard Deviation of Returns (1995) model GARCH Generalized Autoregressive Conditional Heteroskedasticity LSV Lakonishok, Shleifer and Vishny (1992) model
REIT Real Estate Investment Trust
PCA Principal Component Analysis
VAR Vector Autoregressive
UK The United Kingdom
U.S. The Unted States of America

Abstract

This thesis prices, investigates and models market wide herding for selected emerged economies (i.e., U.S. and UK) and named emerging markets (i.e., Taiwan and South Africa) for bonds, equities and real estate sectors. To investigate the mentioned theme/topic, this study develops three hypotheses: (i) the selected indices are prone to market wide herding, (ii) there are systematic volatility patterns during herding process, and finally, (iii) there is positive herding in the real estate sector. The findings are as follows. First, there are persistent herding behaviour of the used indices and moreover, herding behaviour is both within and in between indices. The latter statement is consistent with the findings of Kola (2021). Second, herding exists in volatility towards ~~to~~ the developed economies from emerging markets, irrespective of the product type. Finally, there is definitive herding in the real estate industry, in particular, in indices and not so much in stand-alone REITs. Interestingly, evidence of herding is model sensitive. Finally, the implications are as follows. First, when you invest in bonds, equities and real estate indices, investors should mitigate against herding effects. Second, integration of products, in the context of bonds, equities and real estate, should be encouraged as that increases the levels of information symmetry. The latter statement implies that investing in financial markets would be risky (See; Kola 2021 and Sibongile 2021). Third and finally, intraday investors should have deep insights about emerging markets as emerging financial markets herd towards to emerged markets.

Keywords: bonds, CSAD, CSSD, equities, herding, LSV, real estate, volatility
JEL: G12, G13, G15

1 Introduction

1.1 Background to the Study

With the advent of the dot-com bubble and the stock market crash, investors have been cautionary in where and how they choose to invest~~,~~ (Lin and Li, 2019). The real estate market has incited a great deal of research interest due to the subprime crisis and the behaviour of investors that led to the crisis (Lin and Li, 2019). One aspect of investment behaviour that grows interest is herding behaviour in real estate, specifically in real estate investment trusts (REITs). Studies have shown that herd behaviour can be detected in various markets, including stock markets, commodity markets, oil markets, cryptocurrency markets, and REITs across different volatility regimes (Coskun, Lau and Kahyaoglu, 2020). Coşkun et al. (2020), there is a transition from negative herding behaviour in REITs during low and high volatility periods to positive herding behaviour during crash regimes across various REIT sectors; Lin and Li (2019) investigated herding behaviours within the REIT market, especially in connection with economic policy uncertainty (EPU); Akinsomi et al. (2018), investigated the impact of volatility and equity market uncertainty on herd behaviour in UK REITs during different market regimes from 2004 to 2016, the research focused on understanding how investors and traders exhibit herding behaviour in REITs under varying levels of market volatility; and Akinsomi et al. (2017) found a significant connection between speculative activity in the gold market and herding behaviour in the South African REIT market, particularly during the period from mid-2008 to 2011, following the global financial crisis. This research underscores the relevance of studying herding phenomena within the context of REITs, indicating a notable focus on this area within academic discourse.

Herding is characterised by investors mimicking the actions (selling/buying) of others in a group for some time. These investors dismiss their own information in leu of investments based on the group (Philippas et al., 2013; Dewan and Dharn, 2019; Lin and Li, 2019). Herding behaviour can be spurious or intentional; spurious herding is brought on, when a group has similar decision issues and similar information sets, and each member of the group makes the same or similar decisions independently (Youssef and Mokni, 2021). Intentional herding on the other hand, occurs when the group consciously make decisions /herd similarly to their peers to benefit from the herd behaviour (Youssef and Mokni, 2021).

Herding affects market prices, attributes of risk and thus volatility and return models, ultimately driving fundamental value away (Lin and Li, 2019; Dewan and Dharn, 2019). Intentional herding distorts asset prices because it leads investors to make decisions based on the actions of others rather than on the fundamental value of the assets (Kashif, Palwishah, Ahmed, Vveinhardt and Streimikiene, 2021). This behaviour can result in a feedback loop where investors' decisions are influenced by the collective actions of the market, which may not be sustainable in the long term (Kashif, Palwishah, Ahmed, Vveinhardt and Streimikiene, 2021). As more investors follow the herd, the market's collective actions can drive asset prices away from their intrinsic value, leading to mispricing (Kashif, Palwishah, Ahmed, Vveinhardt and Streimikiene, 2021). Filip and Pochea (2023) opine that spurious herding is related to movements triggered by fundamental information, which implies that it could be a result of investors reacting to changes in the intrinsic value of assets. Therefore, spurious herding could be a response to fundamental value changes rather than a driver that pushes the fundamental value away.

The effects of herding impede the value discovery process of the market mechanism, which disrupts the asset pricing theory because investors ignore private information, which may lead to an augmented demand (Philippas et al., 2013; Dewan and Dharn, 2019). In a volatile market, herding may jeopardise financial stability, and the first adverse market shocks may be intensified by information and augmented by pro-cyclical market mechanisms brought on by herding behaviour (Philippas et al., 2013). Herding behaviour has been identified as a risk amplifier (Cai et al., 2019), with a dynamic nature. Furthermore, herding behaviour has been shown to cause the divergence of market values away from their fundamental values in turn brings about volatility and renders markets inefficient (Yasir and Onder, 2031).

Positive herding is "defined as a group of investors following each other into and out of asset positions, which can be regarded as a market-wide phenomenon." (Fang et al., 2017, pp353). Negative herding is described as the joint actions of a group of investors that go beyond their responses to common news (Fang et al., 2017). Positive herding behaviour affects the cross-sectional return dispersions, whereas negative herding behaviour affects return dispersion across assets or markets (Fang et al., 2017). In equities, positive herding can inflate stock prices, creating bubbles, while negative herding can trigger sharp sell-offs, leading to market crashes. In bond markets, positive herding toward safe assets during uncertainty can lower yields, whereas negative herding from bonds can drive yields higher, especially during rising interest rate environments. For REITs, positive herding can elevate valuations, making it easier to raise capital, while negative herding may lead to undervaluation and capital flight from real estate markets. Across all markets, herding can increase volatility and distort asset prices away from their fundamentals.

Several frameworks have been used to investigate herding behaviour across various markets. These models include the traditional Lakonishok et al. (1992), also referred to as LSV, cross-sectional standard deviation (CSSD), cross-sectional absolute deviation (CSAD), quantile and panel regression.

Market data from investors has illustrated that herding is market-wide across developed, emerging, frontier and global markets (Chen, 2022). Furthermore, some studies have shown that herding effects are likely to appear in emerging compared to developed markets (Philippas et al., 2013; Yasir and Onder, 2023). South Africa and Taiwan are considered major players in their respective geographical markets and are susceptible to global macroeconomic information and changes. (Yasir and Onder, 2023). Emerging markets are known for their underdeveloped financial systems, absence or poorly implemented regulatory frameworks. And a handful of dominant institutional investors and some presence of foreign investment (Yasir and Onder, 2023). When diversifying portfolios with the intention to reduce and mitigate risk, investors may herd due to information in the market. This behaviour may spillover to other markets (assets or countries), which neutralises the intended benefits of diversification (Yasir and Onder, 2023). When herding behaviour occurs across markets, in instances of diversification into new territories behave the same manner with respect to risks such as volatility (Yasir and Onder, 2023). Numerous investigations have postulated that herding is more likely to occur in emerging markets than in developed markets due to the dominance of foreign investors in these developing markets (Yasir and Onder, 2023). The evidence of herding behaviour in emerging markets is relatively unexplored and inconclusive in some ways (Yasir and Onder, 2023).

South Africa and Taiwan are considered financialised emerging market economies (Petry, Koddenbrock and Nölke, 2023). South Africa and Taiwan are regarded as two of the cardinal representatives of emerging markets. Taiwan is one of the oldest emerging markets with a more developed economy. The U.S. and the UK are two of the largest world economies by GDP, both members of the G7 and have strong economic and trade ties.

The intended significance and contribution of the study is to extend the analyses of herding behaviour of the global market. The study beckons a dataset from several countries due to the heterogenous behaviour among investors; thus, data from a single market would be vexing, ergo avoiding sample bias (Yasir and Onder, 2023). Lastly, the study intends to demonstrate that this behavioural phenomenon disobeys the modern portfolio theory.

1.2 Substantiation of the Problem

This study intends to analyse herding behaviour and its effects on the listed property market, especially the REIT market. Real estate seems to have a low correlation with stocks and bonds and has contributed positively to portfolio optimisation. Real estate can serve as a type of consumption commodity and an investment tool, the risk-return profile of real estate differs from that of the underlying stock markets (Lin and Li, 2019). Therefore, the performance and investment dynamics and real estate-stock link are not theoretically expected to be similar, which requires separate empirical investigations (Lin and Li, 2019).

Furthermore, the study will highlight the asymmetry of herding behaviour and its impact on the price discovery mechanism. The study will also explore the spillover effects over three asset classes: bonds, equities, and listed real estate. There has been evidence of herding spillovers from U.S. corporate bonds to U.S. equities; the spillover has shown to be one-sided and time-period specific (Starkey and Tsafack 2023).

Financial markets (real estate, equity, bond and money markets) are interconnected through information and volatility linkages, particularly during periods of exogenous shocks, with implications for asset allocation, cross-market pricing and hedging, and policymaking. Research across these asset classes support the development of balanced investment markets and may assist in economic recovery efforts and strategies post-exogenous shocks (Wang, Tomlins and Tiwari, 2023).

1.3 Problem Statement

Literature has suggested that herding behaviour is more likely to persist in emerging markets than in developed markets (Zhou and Anderson, 2013). Herding behaviour and its effects have been studied in developed markets, but the behaviour has yet to be extensively investigated in emerging markets. Previous investigations have concentrated on herding spillover effects from one country to another (Chiang and Zheng, 2010). However, there are limited studies on cross-asset class herding spillover effects (Starkey and Tsafack 2023).

1.4 Primary Research Question

The primary research question is how does herding behaviour affect market returns in developed and emerging markets?

1.5 Secondary Research Questions

From the primary question, the secondary research questions are identified as follows:

- What are the determinants of herding in bond, equity and real estate markets?

- How is herding behaviour affected by volatility in the corporate bond, equity and real estate markets?
- Is there herding behaviour in the real estate markets?

1.6 Research Aim

This research investigates the effects of market-wide herding behaviour on market volatility and values in developed markets (the U.S. and the UK) and emerging markets (South Africa and Taiwan).

1.7 Research objective

From the aim, the following research objectives are identified:

- To detect determinants of herding developed and emerging markets.
- To examine the impact of market volatility on herding behaviour
- To determine herding behaviour in the real estate markets.

1.8 Research Gap

Prior studies that explored herding behaviour among different asset classes mainly share prices (Ro and Gallimore, 2014). Furthermore, those studies that explored herding hardly explored different geographies simultaneously around the world (Martins et al. 2020). Therefore, this study explores herding behaviour among indices (bonds, equities and listed real estate), specifically comparing two developed and two emerging economies. The choice of the countries will be explained later in the data section.

1.9 Assumptions

The following assumptions have been made in this study:

- The returns data collected will be a true and accurate indication of the performance of the asset classes being investigated.
- The current tools in herding analyses need to be improved in some respects; the study will attempt to use alternate tools to extend the analyses of herding behaviour.

1.10 Hypotheses

The following hypotheses have been made in this study:

- Hypothesis one seeks to elucidate the drivers of herding behaviour. This will be achieved by extracting the major contributing factor to a causal effect (Kola, 2017).
- The second hypothesis seeks to clearly illustrate the apparent relationship between herding behaviour and volatility across different market regimes. Studies have shown that volatility may occur before or after herding, and it is essential to empirically demonstrate this relationship to determine whether herding can be hedged or diversified. We use the Markov regime-switching approach to investigate the cross-country herding effect; it also captures different market regimes and herding that may prevail in varying markets.
- Lastly, hypothesis three will illustrate will test for herding behaviour using the traditional three herding tests: LSV, CSSD, and CSAD.

2 Behavioural Theories

2.1 Introduction

A well-documented behavioural theory can be traced back to Watson (1913). He opined that behavioural theory within psychological framework is simply a branch of natural science. Furthermore, the author stated that at the heart of behavioural theory is prediction and control of behaviour. In the context of financial markets, behavioural theory can be traced back to Adam Smith in the 18^{th} century. At that point in time, the behavioural theory in the context of financial markets was known as behavioural economics, which is linked to the economic psychology. Given that the 18^{th} century was the height of the classical economic theory, behavioural economics is largely influenced by the classical economic theory (See; Kahneman 2003). Later on, behavioural finance emerged in the 1970s and the latter theory focused on the psychology of investors or analysts. Within capital markets, behavioural economics and behavioural finance comes in different forms. According to Bae et al. (2019), the collective behaviours that are observed in nature and seen in society are (i) aggregation, (ii) fads, (iii) fashion, (iv) flocking and (v) herding. This thesis is centred on herding behaviour; therefore, the following chapter gives an overview of the other four types of collective behaviours. This is because herding can be replicated into other similar strategies (See, Merkle 2018).

2.2 Collective Behaviours

The traditional finance outlook postulates that economic and financial decision are undertaken by rational participants who make use of perfect market information in order to generate unbiased and objective forecasts about the future of markets (Taffler, 2018). Anomalies such as the global financial crisis emerge and persist and cannot be explained through the traditional finance lens because the participants are inherently not rational and behavioural finance aims to explore these anomalies and the decisions by the irrational market participants (Taffler, 2018). During times of financial instability or crisis financial networks synchronize at a higher degree than normal, stock prices move in a similar manner which defines the markets direction and collective behaviour has emerged (Stosic et al, 2018).

2.2.1 Aggregation

Information aggregation occurs when market participants amalgamate scattered information into clear price signals in terms of an asset’s fundamental value. Information aggregation is realized when the market is filled with traders that appreciate and infer other trader's private information (reflective traders) from trading prices (Eyster et al, 2019). Thus, our understanding of information aggregation in markets may be improved by considering the cognitive and reflective skills traders need to infer other traders' information from asset prices (Corgnet et al, 2021 and Eyster et al, 2019). Efficient information aggregation is achieved when all market participants have a significant degree of cognitive sophistication and this significant degree of cognitive sophistication is common widespread across all participants (Corgnet et al, 2021). The composition of traders also impacts information aggregation; an overconfident trader overweighs their own private information but accurately estimates the precision of other trader's private signals. Thereafter, the price overreacts to private signals and, inversely dismissive traders underreact to private signals and the price underreacts (Eyster et al, 2019).

One of the downfalls of information aggregation is that it is not possible to accurately observe market traders' private information thus aggregation falls void of the Efficient Market Hypothesis (EMH hereafter) (Corgnet et al, 2021). An additional impediment to the aggregation of information is herding where individuals making sequential decisions opt to rationally dismiss their own private information and move with the majority (Corgnet et al, 2021 and Eyster et al, 2019). On the positive side, information aggregation provides enough evidence to encourage regulators to impose some form of financial training and sophistication for individuals that open trading accounts to lessen the degree of asset price distortion.

2.2.2 Fads and Fashions

Fads and fashions are considered rapid and short run fluctuations, apparent idiosyncratic swings in mass behaviour without any clear external stimulus, this behaviour changes without any apparent reason (Schleifer and Summers, 1990). Fads and fashions occur when changes in expectations or sentiment which are not backed by information, but pseudo-signals believed to relay information about future returns, but that would not convey such information in a fully rational model (Schleifer and Summers, 1990). Trading strategies based on pseudo-signals, noise, and popular models are correlated, leading to aggregate demand shifts (Schleifer and Summers, 1990). Furthermore, fads and fashions are considered mean reverting from the intrinsic value (Schleifer and Summers, 1990).

Fads and fashions lead to the distortion of asset prices away from their fundamental values as a consequence of social, psychological switch in market sentiment and school of thought (Bikhchandani et al, 1992). Bikhchandani et al (1992) purports that information cascades can explain rapid and short-lived fluctuations such as fads, fashions, booms, and crashes**.** Information cascades occur when an individual observes the actions/behaviour of those preceding them follows the behaviour of the individual before him with complete disregard of their own information (Bikhchandani et al, 1992).

Compared to rational speculative bubbles, however, the change in asset prices induced by fads and fashions do not stray from its fundamental value unlike a rational speculative bubble. In these models the asset price does not deviate from its fundamental value in an eruptive way (Bikhchandani et al, 1992). Fads and fashions may introduce ambiguity in the management strategies of funds, the ambiguity may not necessarily be detrimental but may offer a source of market dynamism. This is because those two mechanism may encourage market innovation and transform what is typically viewed as acceptable market practice (Nath, 2021).

Because fads and fashions are steadily mean reverting thus, they can be considered almost rational market participants wait awhile before they can make use or act on their knowledge that their prices are in fad/fashion. Fads and fashions disadvantage investors and markets as a whole because they may appear to be legitimate and innovative systems that will revolutionise the future of money and currency (Shahzad et al, 2019). One such example is Bitcoin.

Furthermore, fashion is viewed as drastic, short-lived fluctuations in a market where market novices follow market leaders; it is sometimes driven by sentiment and void of market fundamentals (Spyrou, 2020). Fads and fashions are generally described and mentioned interchangeably.

2.2.3 Flocking

The flocking mechanism has been used in a variety of models of biological, sociological, and physical aggregation phenomena (Bae et al, 2020). Flocking is described as an ordered movement, which individuals or investors organize themselves through limited information and simple rules or models (Ha and Tadmor, 2008). The flocking Cucker and Smale model is a popular framework that captures flocking behaviour by quantifying the tendency of individual groups adjust their velocity to the combined group average velocity where all groups move at the same velocity through weighted communication (Cucker and Smale, 2007). Bae et al (2020) went further and characterizes flocking as a behaviour, with no inherent intended direction or absolute and unequivocal navigation.

The description above of flocking illustrates a few disadvantages that may be associated with flocking behaviour; (i) investors make decisions with little to no information purely to assimilate with the rest of the group of investors, this behaviour can inflate/deflate asset prices or create bubbles, (ii) due to the fact that flocking is underpinned by investors reaching a consensus without a predetermined or true direction, asset prices and the market become very difficult to predict. The advantages of this flocking behaviour include the behaviour is able to correct ‘bad/ill-mannered’ decisions made by a few investors that may have destabilised the market.

2.3 Herding

Herding behaviour has been purported to impact market movements throughout time from the Dutch tulip mania in the 1630s, to the events that lead to the 2007 housing market crisis, as well as the dot-com bubble in the 2000s (Bouri et al, 2019). Herding behaviour occurs when investors ignore their personal information and imitate the investment decisions of other investors, this behaviour impacts risk-return trade-off and thus the asset pricing model (Bouri et al, 2019). In previous studies on herding behaviour has been able to explain bubbles as well as crashes in the market, and more recently in the cryptocurrency market (Bouri et al, 2019). Policy makers have also taken note and interest in the study of herding due to its ability to intensify volatility of asset returns and destabilize the financial system (Bouri et al, 2019). Academics and practitioners have studied herding behaviour because it challenges the efficient market model because investors hide their private information which distorts fundamental market information and inhibits the ability to forecast (Bouri et al, 2019 and Yousaf et al, 2018).

The focus on this study will centre on herding behaviour. The study will explore herding behaviour among indices (bonds, equities and listed real estate), specifically comparing two emerged and two emerging economies.

2.3.1 Proposed Analysis of Herding

Herding methodologies explore how investors follow the actions of others rather than relying on their private information (Bouri et al, 2019). Several models capture this behaviour across different markets, and they are interconnected through their focus on return dispersion and patterns in buying and selling. These methodologies will be explored, and their connectedness will be discussed below. The discussion will commence with the traditional herding measures followed by the additional measures that will be used to provide a comprehensive analysis of herding behaviour.

Lakonishok, Shleifer, and Vishny (LSV) Model:

- Focus: Developed by Lakonishok et al. (1992), the LSV model measures herding by looking at how institutional investors buy and sell a stock in the same direction (e.g., many managers buying or selling simultaneously). This model assumes herding exists when investors trade heavily in the same direction.
- Application: The LSV model was initially applied to stock prices but later extended to bonds and real estate indices, as done in studies comparing developed markets like the U.S. and the UK with emerging markets like South Africa and Taiwan.

Cross-Sectional Standard Deviation (CSSD) Model:

- Focus: Proposed by Christie and Huang (1995), this model measures the dispersion of individual stock returns relative to the market. The greater the dispersion, the less herding is observed. Conversely, when returns move closer together, herding is likely.
- Application: CSSD is commonly used to detect herding during periods of market stress, such as bull or bear markets.
- Interconnection: The CSSD model is complementary to the LSV model, as they both measure herding but from different perspectives. LSV looks at behaviour in the number of buyers and sellers, while CSSD focuses on return dispersion.

Cross-Sectional Absolute Deviation (CSAD) Model:

- Focus: Chang et al. (2000) proposed this model, which modifies the CSSD by including a nonlinear component to better capture herding. The CSAD assumes herding is stronger when market movements are extreme and adds a quadratic term to model this behaviour.
- Application: CSAD has been widely used to study herding in developed and emerging markets, especially during times of market volatility or uncertainty. Studies often compare CSAD results with CSSD to test for robustness.
- Interconnection: The CSAD model builds on the CSSD by incorporating nonlinear effects, making it a more sophisticated tool for detecting herding. Both models are typically used together to validate findings from one another.

All these models share a common goal: understanding how investor behavior departs from rational, independent decision-making during market stress or uncertainty. While LSV focuses on institutional behavior, CSSD and CSAD capture patterns in return dispersion. The findings across these models tend to align, especially in confirming herding's tendency to emerge more prominently in volatile or uncertain periods, and they are often used together to verify the robustness of herding results.

The Principal Component Analysis (PCA hereafter), Generalized Autoregressive Conditional Heteroskedasticity (GARCH hereafter), Vector Autoregression (VAR hereafter), and the Markov Regime Switching (MRS hereafter)—support the detection and analysis of herding behavior by modelling volatility, interdependencies, and regime shifts in financial markets.

<u>Principal Component Analysis (PCA):</u>

- Focus: PCA is a statistical technique used to reduce the dimensionality of large datasets by transforming them into a set of principal components that capture the maximum variance in the data. In the context of herding, PCA identifies the key variables (e.g., macroeconomic factors, market indices) driving herding behavior across different markets (e.g., equities, bonds, real estate).
- Application: PCA helps simplify the analysis by extracting the most important factors contributing to herding behavior. Instead of analyzing hundreds of variables, PCA reduces them to a few principal components that explain most of the variance.
- Interconnection: PCA is often used before applying models like GARCH, VAR, and MRS to reduce complexity and focus on the main drivers of herding behavior. For example, PCA can identify key factors (e.g., volatility, market sentiment) that drive herding across multiple asset classes, which can then be further explored with GARCH, VAR, etc.

<u>GARCH (Generalized Autoregressive Conditional Heteroskedasticity):</u>

- Focus: GARCH models are used to analyze time-varying volatility in financial markets. They capture how current volatility is influenced by past volatility and returns, making them crucial in studying market behavior during periods of high volatility when herding is most likely to occur.
- Application in Herding:
    a) Volatility Clustering: Herding often leads to volatility clustering—where periods of high volatility are followed by more high volatility. GARCH can model this clustering effect, providing insight into how herding amplifies market risk, especially in times of uncertainty.
    b) Complementary to CSAD: The GARCH model can work alongside CSAD by explaining why herding is more pronounced in volatile markets. If GARCH detects

persistent volatility, the CSAD model may reveal stronger herding behavior during these times.

c) Empirical Support: For example, studies using GARCH confirm that periods of high volatility in REIT markets are associated with increased herding behavior, as investors tend to follow others to mitigate perceived risks.

VAR (Vector Autoregression):

- Focus: VAR models capture the dynamic interrelationships between multiple time series (e.g., returns of bonds, equities, and real estate indices). VAR can model how shocks in one market (e.g., equities) spill over into others (e.g., real estate or bonds), revealing cross-market herding behavior.
- Application in Herding:
  a) Interdependencies and Spillovers: VAR is critical for identifying herding across markets. For instance, if a shock in the bond market causes correlated movements in real estate and equities, VAR helps explain this spillover effect, supporting the idea of cross-asset herding. In this way, it complements models like LSV that examine institutional behavior across multiple asset classes.
  b) Herding Across Countries: Herding often manifests across markets and geographies, as shown in research on U.S., UK, South African, and Taiwanese indices. VAR models have revealed that herding behavior in one country's market can influence another, confirming cross-border herding.
  c) Robustness Testing: The use of VAR, as in your research, allows for robustness testing of herding behavior across different markets, supporting the results from LSV, CSSD, and CSAD models by showing that herding is not isolated but part of a broader market interaction.

MRS (Markov Regime Switching):

- Focus: MRS models capture how financial markets switch between different regimes, such as periods of high volatility (crisis) and low volatility (stability). These regime shifts are often associated with changes in investor behavior, including herding.
- Application in Herding:
  a) Regime-Dependent Herding: Herding behavior can vary depending on market conditions. MRS models are particularly effective in detecting herding during crisis periods (e.g., when markets are in a high-volatility regime). They complement

herding models by explaining that herding intensifies during crisis regimes and diminishes in stable periods.

b) Nonlinearity: Since herding behavior is nonlinear and often depends on market sentiment or external shocks, MRS is a valuable tool for detecting how investors switch between herding and non-herding behavior as regimes change. This can be linked with the CSAD model's ability to capture nonlinearity in return dispersions.

c) Volatility and Herding: By identifying regime shifts, MRS can reveal that periods of increased herding behavior are associated with certain market regimes, often when volatility spikes. GARCH models may explain the volatility, while MRS pinpoints the regime in which herding is most pronounced.

2.3.2 How They Complement One Another

- PCA reduces the complexity of the dataset by identifying the key factors (e.g., volatility, interest rates, macroeconomic shocks) driving herding behavior across markets.
- GARCH models the time-varying volatility of the principal components identified by PCA, showing how volatility affects herding.
- VAR analyses the dynamic interrelationships between these principal components, revealing how herding spills over between markets and asset classes.
- MRS tracks how herding behavior changes across different market regimes, as driven by the principal components identified by PCA (e.g., high-volatility or crisis periods).
- LSV, CSSD, and CSAD quantify herding behavior by measuring how institutional investors' buy/sell decisions or return dispersions evolve in response to the factors identified by PCA.
- GARCH identifies periods of increased volatility, which are often precursors to herding behavior. It explains why herding tends to happen during market turmoil, as volatility makes investors more likely to mimic others.
- VAR captures the dynamic interactions between asset classes or markets, showing how herding can spill over from one market to another. This highlights the interdependencies in global markets and helps explain how herding spreads across different sectors.
- MRS identifies market regimes, helping to pinpoint when herding is most likely to occur. By modelling shifts between high- and low-volatility regimes, MRS shows how herding behavior changes in different market conditions.

~~3~~ Herding Behaviour at the Index Level

3.1 Introduction to Index Herding Behaviour

Herding behaviour is nothing new in capital markets; however, when real estate assets are taken into account, literature on that is very thin. Numerous scholars have investigated herding behaviour, raising key issues in the process; (i) any skill involved in herding behaviour (Jiang and Verado, 2018), (ii) its effect on investment, based in transatlantic nations such as emerging markets (Rahayu et al, 2021) and (iii) benefits of herding behaviour (Omay and Iren, 2019). Prior studies explored herding in the context of asset management portfolios made up of cash, bonds and equities. When one adds real estate among other asset classes to a portfolio in asset management, then one is moving into an alternative investment.

In alternative investing, unlike in asset management, one focuses on minimising risks as opposed to increasing returns in asset management. Broadly, real estate, in particular REITs have been found to have diversification benefits-see Benefield et al. (2009). Some earlier studies on listed real estate, such as REITs focus on benefits of real estate in the traditional asset management approach, where the portfolio is mainly of real estate nature.

When listed real estate is invested in a portfolio that includes bonds and equities, several questions arise. Does one experience unique herding when investing in listed real estate, bonds and equities indices? Given that real estate is generally heterogeneous in nature, how does it affect herding when included in a portfolio made up of bonds and equities indices? Lastly, how different is herding behaviour, when one compares developed and emerging markets? The contribution of this study is exactly responding to the questions posed above.

The article close to this study is Marcato and Nanda (2016). The authors investigated herding behaviour based on survey-based sentiment indices for the United States of America (U.S.) for different periods-for residential properties; data is from 1988 to 2010 and for non-residential properties from 1997 to 2010. This article uses market-based indices of selected countries. The advantage of market-based indices is that they encompass every parameter of the stock markets (Yu et al, 2020). Marcato and Nanda (2016) focused on (i) supply-side players (homebuilders, architecture firms, etc.) and demand-side suppliers (consumers/home buyers). They argue that at the centre of herding behaviour in real estate is (i) asymmetric information, (ii) infrequent and lumpy investment and (iii) long-term commitment. Unlike Marcato and Nanda (2016), this study explores herding behaviour of bonds, equities and listed real estate. In order to model the herding behaviour, Marcato and Nanda (2016) used (i) vector autoregressive (VAR) model, (ii) Cholesky decomposition and (iii) principal component analysis (PCA). The results of Marcato and Nanda (2016) confirm that sentiments influence herding behaviour. Insofar sentiments are concerned; informational content is stored in sentimental indices. And, that informational content is most likely to influence future investment behaviour of some investors. Overall, the residential housing market exhibit herding behaviour among different investors is in residential property market. The author went further and did robustness tests based on diagnostic tests [(i) augmented Dickey-Fuller test; from here ADF; (ii) Akaike, Schwarz-Bayesian and Hannan-Quinn criteria, (iii) Wald test and (iv) Granger test]. The diagnostic tests confirmed the earlier findings of Marcato and Nanda (2016). Further robustness included using valuation indices (i.e. NCREIF property index) and the results of NCREIF confirm the findings of sentiments indices.

Fundamentally, the results show that herding behaviour is largely driven by existing relationships between countries. The more there are similarities between partner countries, the higher are the chances of herding behaviour from same and/or similar assets-equities indices of the U.S. and the UK, and so are their listed real estate indices. Interestingly, South African indices do not exhibit any herding behaviour with indices of the selected countries. Furthermore, there are spillovers of herding in between and across the U.S. and the UK. The robustness tests as measured by VAR model confirm the findings of the principal component analysis (PCA).

The balance of the study is structured as follows. Section 3.2 is on literature review. Section 3.3 is on data. Section 3.4 is on the analysis and the final section concludes the study.

3.2 Literature Review

3.2.1 Bonds

Herding has been flagged as a significant risk amplifier in the corporate bond market (Cai et al, 2019). It has been found that institutional herding is more prevalent in the bond market especially with the speculation-grade bonds (Cai et al, 2019). The price impact of institutional herding in the bond market has presented asymmetric findings, on the buy and/or sell herding, which cause price destabilization. This is seen in the price reversal observed within six quarters of the herding behaviour (Cai et al, 2019). Cai et al (2019) sought to find out if institutional investors exhibit herding behaviour in fixed-income markets and whether herding in the bond market destabilizes bond prices. Literature on herding by institutional investors in the bond market has been proven to be limited with varied results (Cai et al, 2019). The study was conducted using various tools to reach its objectives; the Lakonishok et al (1992) (henceforth LSV) method was first used to approximate the magnitude of institutional herding, then panel regression was used to assess the determinants of herding and how the herding differs with varying bond attributes and their past performance. Lastly, the price impact was evaluated by applying a portfolio approach which helped shed light on the provenance of herding (Cai et al, 2019).

The study assessed three types of institutional investors, namely: mutual funds, insurance companies and pension funds. The secondary data for the study was collected from multiple sources, data on institutional investors that hold corporate bonds from Thomson Reuters Lipper eMAXX. The data holds quarter-end security-level corporate bond holdings of three classes: insurance companies, mutual funds, and pension funds. Data was also collected from the Fixed Investment Securities Database for additional bond and issuer information (Cai et al, 2019). Lastly, bond pricing data was collected from the Bank of America Merrill Lynch's Corporate Bond Index Database which contains daily closing bid prices and is a good representative pool of U.S. public corporate bonds. The data covered a period from the third quarter of 1998 to the third quarter of 2014.

Cai et al (2019) found that herding occurs more in corporate bonds compared to equities, more notably with speculative bonds. Insurance companies have a higher propensity to herd as compared to pension and mutual funds, with sell herding being more vehement than buy herding (Cai et al, 2019). Key drivers of institutional herding in the bond market include rating changes, past bond performance and bond liquidity (Cai et al, 2019). The non-linear herding-to-performance results presented by Cai et al (2019) are similar to the results by (Goldstein et al, 2015). The latter study found that bonds that have performed badly in the past correlate with inordinately large sell herding. Furthermore, Cai et al (2019) found a significant imitation-driven intertemporal herding in bonds. Due to its disruptive impact, sell herding may be a great risk to financial stability (Cai et al, 2019). Sell herding causes significant price distortions due to its short-term price effects which in turn may lead to excess price volatility. On the other hand, buy herding leads to permanent price impact which aids with price discovery (Cai et al, 2019). Sell herding is mainly found in junk, small and illiquid bonds, and during the subprime crisis (Cai et al, 2019).

Market commentators and other financial stakeholders believe that illogical herding behaviour was the irrational herding behaviour was the principal element that led to the European financial crisis and the resultant turmoil (Galariotis et al, 2016). If it is put forward that herding behaviour, then stocks may herd in one of the three ways: 1) the irrational plane which investigates investor psychology and suggests that individuals copy one another, 2) the near-rational plane claims that investors apply a set of rules to ascertain data easily, and 3) the rational plane keeps the position that herding behaviour may be a result of flawed data, reputation and compensation issues (Galariotis et al, 2016).

Galariotis et al (2016) investigated the presence of herding in the European government bond market. The investigation aims to empirically show evidence of the type herding behaviour that may have presented itself during the Europe financial crisis because various market participants have assumed that the EU crisis was intensified by irrational herding behaviour (Galariotis et al, 2016. Herding behaviour is tested against the release of macroeconomic data; changes in the U.S. federal fund rate, the Bank of England base rate, European Central Bank rate and the period that the macroeconomic data is released in the European region (Galariotis et al, 2016). Furthermore, the study was split into three periods; before, during and after the financial crisis because, Christie and Huang (1995) postulate that herding may occur during a time of significantly big market swings and to discern if herding escalates during the financial crisis or not (Galariotis et al, 2016). Lastly, the authors investigate if there are herding spill-over effects between the markets that are in financial disarray and those that are not experiencing any financial crisis, because it was found that in equity markets that events in one market can help explain herding behaviour in other markets (Chiang and Zheng, 2010; Klein, 2013).

The study analysed daily clean prices for the 10-year Government Benchmark Bond Indices for the following EU countries: Germany, Spain, Italy, France, Austria, Belgium, Finland, Greece, Ireland, the Netherlands and Portugal. The data covered a period over 13 years from January 2000 to January 2013. The data was sourced from DataStream International. The sample countries are divided in two sub-sets: the first one consists of the Eurozone countries that run into financial difficulties during the recent crisis (Portugal, Ireland, Greece, Spain) with the addition of Italy (denoted for simplicity as the Southern markets, hereafter), while the second contains the rest of the Eurozone member states (Austria, Belgium, Germany, Finland, France, the Netherlands; denoted for simplicity as the Northern markets, hereafter). The study period was divided into before the financial crisis, which was from January 2000 to December 2006 and during the financial crisis, which was from January 2007 to January 2013. The sub-periods were further divided into days that the market portfolio performance was positive and days the market portfolio performance was negative to elucidate any asymmetries (Galariotis et al, 2016). The investigation made use of the Cross-Sectional Absolute Dispersion (CSAD) model and the market performance or return in order to detect herding behaviour and carry out the investigation.

Galariotis et al (2016) found no evidence of herding behaviour before and after the financial crisis. There was finite statistical evidence of herd behaviour in the EU government bond prices, preceding and following the European debt crisis (Galariotis et al, 2016). Nevertheless, after further tests, the study found that during the financial crisis when macroeconomic data is accounted for, there was no evidence of herding when the European Central Bank rate changed (Galariotis et al, 2016). Thus, supporting the notion of herding motivated by changes in fundamentals, fundamental-driven herding (Galariotis et al, 2016). The study also revealed that there were herding spillover effects, in the opposite direction, from EU markets with no financial issues to EU markets in financial crises (Galariotis et al, 2016).

Czech and Roberts-Sklar (2019) investigated trading volumes of corporate bonds as a result of a change in yields. The corporate debt market plays a pivotal part in the global financial system by supplying the real economy with funding (Czech and Roberts-Sklar, 2019). Czech and Roberts-Sklar (2019) attempt to provide a glimpse into the investment behaviour of the U.S. secondary corporate bond market, when large investors were to behave in a procyclical manner-i.e. selling bonds as prices fall and buying as prices rise-they might amplify yield moves, potentially causing markets to overshoot.

Abrupt and steady declines in the price of corporate bonds affects the capabilities of firms to come up with funding, which may impact how the firm’s decisions are made and may jeopardize their solvency (Czech and Roberts-Sklar, 2019). It is thus important to investigate how end investors behave in that situation. The investigation by Czech and Roberts-Sklar (2019) analyse the heterogeneity in investment behaviour on a relatively high frequency and across different investor types: dealer banks, non-dealer banks, insurance companies, hedge funds and asset managers. Czech and Roberts-Sklar (2019) assessed investor behaviour in the sterling corporate bond market by regressing the logarithm of buy and sell volume on the lagged change in bond yields, controlling for a range of factors. The study is over a period of 7 years, from September 2011 to December 2016 from the propriety Zen database which are trading in sterling corporate and government bonds for all firms regulated in the UK, or branches of UK firms regulated in the EEA (Czech and Roberts-Sklar, 2019).

Czech and Roberts-Sklar (2019) found that hedge funds, insurance firms, and asset managers increase their acquisition and reduce disposal of sterling corporate bonds remarkably after a rise in corporate bond yields. It was also found that dealer banks clear the market by reducing acquisitions and increasing disposals (Czech and Roberts-Sklar, 2019). The study found that the firm’s behaviour is reversed in times of market stress, such as the 2013 taper tantrum, asset managers sold more and bought less in response to a rise in yields, which may have amplified yield changes (Czech and Roberts-Sklar, 2019). Asset managers may face incentives to behave procyclically in stress periods given their exposure to short-term benchmarks and redemption risk (Czech and Roberts-Sklar, 2019). At the same time, dealer banks who were net buyers, clear the market. This is consistent with theoretical postulations that banks behave countercyclically during stress periods in fixed-income markets (Czech and Roberts-Sklar, 2019).

Yang et al (2019) examined how information and/or announcements from the Korean corporate bond market affects the trading volumes of the stock market, the study assessed how the stock market reacts to corporate bond (credit) rating change announcements. As well as changes in stock prices and investor behaviour with regards to trading volumes and trading patterns, in the Korean market, which has been shown to exhibit significant information asymmetry across different investor groups (Yang et al, 2019). The investigation seeks to assess whether or not information asymmetry over several different investor groups exists around bond rating change announcements. If they do, whether or not this informational advantage is utilized to achieve abnormal stock returns (Yang et al, 2019).

Several studies have investigated how changes in the bond rate effect the stock market behaviour (stock returns and trading volumes) but not much is known about investor behaviour due to information asymmetry (Yang et al, 2019). Korea is the fourth largest bond market globally with regards to its trading volumes, little focus has been given to assessing the behaviour of emerging stock markets, including that of the Korean market, with respect to changes to bond rating announcements (Yang et al, 2019). The Korean credit rating agencies have consistently endeavoured to enhance their rating quality through strategic alliances with the major international agencies, such as Moody's and Fitch (Yang et al, 2017). Considering the size of the Korean stock and bond markets and the world-class standard rating the quality of the rating agencies, it is worth examining the informational effect of bond rating changes on the Korean market (Yang et al, 2019). The Korean financial market has a distinct framework in that domestic individual investors are generally considered uninformed traders and that cause noisy and speculative trades, and those type of traders are major market participants (Yang et al, 2019). However, developed financial markets, such as the New York Stock Exchange, are mainly led by institutional investors (Yang et al, 2019).

The data was collected from firms on the KOSPI which have been rated by Korea Investors Service, NICE Investors Service, or Korea Ratings. This study used daily stock transaction data between January 2000 and December 2015. Trading volumes and investor behaviour was measured by estimating the abnormal returns, abnormal volume, and net order imbalance around rating change announcements and identify the trading patterns of different investor groups (Yang et al, 2019). The stock price response to bond rating changes is estimated using the abnormal returns of individual securities based on the market-adjusted model (Yang et al, 2019). The average abnormal returns are summed over a given period to yield cumulative average abnormal returns (Yang et al, 2019).

Yang et al. (2019) set out to measure whether and to what extent information asymmetry exists between different investor groups, stock price reactions to rating changes and the trading behaviour of different investor types around the rating changes (i.e. trading-volume responses and order-imbalance responses) are examined. The results of the investigation show that abnormal stock returns are significantly positive around upgrades and negative around downgrades (Yang et al, 2019). But a closer look at the results, suggests that the impact of rating changes on stock prices is stronger around downgrades (Yang et al, 2019). Furthermore, abnormal trading volumes are detected around rating changes, and net order imbalances are found to vary by investor type, both of which reflect differences in trading behaviour by different types of investors in response to a rating change (Yang et al, 2019). Particularly, foreign (domestic institution) investors make capital gains through buy (sell) orders around upgrade (downgrade) announcements, whereas domestic individuals exhibit a relatively inferior trading performance by placing more sell (buy) orders around upgrade (downgrade) announcements. These opposite trading patterns across distinct investor groups support the information superiority (inferiority) of institutional (individual) investors (Yang et al, 2019).

Cai et al (2012) postulate that herding behaviour is a notable trait of institutional trading, this is a big concern for critics and stakeholder due to the destabilizing effect herding has on security values. It is important to understand how institutional investors trade securities and how this impacts asset valuations, managing risk, and managing the regulation of the corporate bond market (Cai et al, 2012). Literature has shown considerable attention to post-herding returns and have provided evidence that security prices follow in the herding direction. Some studies have provided contradictory evidence and have shown return reversals after acute institutional trading (Cai et al, 2012). Cai et al (2012) investigated corporate bonds that operate in a decentralized market where participants trade securities directly between two parties without a central exchange or broker-the Over the Counter (OTC) market. OTC markets are known to have liquidity and high information asymmetry.

Cai et al (2012) studied trading by institutional investors in the U.S. corporate bond market, with a focus on their herding behaviour. The study data was sourced from databases: pricing data was sourced from Merrill Lynch's Corporate Bond Index Database, data on the corporate bond holdings by investors was sourced from Thompson Reuters/Lipper eMaxx Fixed Income Database (Lipper Data). The corporate bond data for analysis was collected from the TRACE which has record of the corporate bond transaction data and data on U.S. corporate bond holdings by institutional investors. The total sample for the study comprised of 17,771 distinct bonds over a period of 6 years from 2003 to 2008.

The study found correlated trades in the bond market using the LSV model, there was substantial institutional herding considerably higher than herding recorded in the equity market (Cai et la, 2012). The investigation found that sell herding spikes when negative data on bond ratings and corporate earnings are released then. Buy herding spikes with the release of trade data from the Trade Reporting and Compliance Engine (TRACE). The study found that herding behaviour persists in small bonds, that have low ratings with higher data asymmetry, which are conditions characterised by the OTC market. The third driver of herding was found to be a phenomenon called mimicry which displays itself in the following ways: 1) buy herding increases within the first quarter, 2) over a period of quarters there is a significant correlation between current and past trading of institutional investors (Cai et al, 2012).

Findings of the investigation revealed that there is significant return reversals post-herding largely in the for sell herding, thus sell herding distorts bond values and may cause volatility in the bond market. When institutional investors herd to sell bonds with low liquidity there is a high probability that price reversal will occur which indicates that temporary price pressure is the cause of the price reversal (Cai et al, 2012).

3.2.2 Equities

There have been widespread studies on behavioural finance which provided substantial evidence of the presence of herding internationally for a wide cross section of markets. Both developed and emerging and has shown that the significance of herding is a function of a series of factors and market states (Guney et al, 2017). However, not much is known about herding behaviour and what triggers this behaviour in a group of markets named the frontier markets despite the global interest by international portfolio investors for diversification gains due to their low correlations with the international markets (Guney et al, 2017). Though these frontier markets have seen an efflux of international portfolio investments in the past decade, is evident as shown by mutual funds and exchange traded funds launched with an explicit focus on frontier market equities (Guney et al, 2017).

These frontier markets have financial markets are currently characterized by incomplete and ill-enforced institutional frameworks, and low transparency levels (Guney et al, 2017). These conditions discourage local and international investors from engaging in these financial markets, the result being that most frontier equity markets are small, very highly concentrated and illiquid, with very low levels of capitalization and trading volume (Guney et al, 2017 and

Marshall et al, 2015). Thus, the trading volumes and patterns in these frontier stock exchanges causes hindrances in the generation (given the low investors' participation and trading activity) and quality (due to the low transparency) of information (Guney et al, 2017).

The study collected daily data observations on closing prices and market capitalization values for the period between January 2002 to July 2015 from the following eight African equity markets: BRVM, Botswana, Ghana, Kenya, Namibia, Nigeria, Tanzania and Zambia. The data was collected from the Thomson-Reuters DataStream database. The study made use of the CSAD model to capture herding through a non-linear empirical specification.

Herding was found across all eight financial markets due to the low transparency levels which reduce the quality of the informational environment, and leads to investors viewing herding a feasible option, allowing them to infer information from their peers' trades (Guney et al, 2017). Guney et al (2017) found that herding does not exhibit significant asymmetries conditional on different market states; this is the case, particularly, with market returns, where herding appears significant irrespective of the market's directional movement in most cases. The herding did exhibit asymmetric behaviour with respect to market volatility, as it appears significant (or stronger, compared to high volatility days) mainly during days of low volatility; however, it is weaker during crises times as seen in the sample during the 2007–2009 global financial crisis (Guney et al, 2017).

Domestic herding was found to be significant across all eight markets, the same does not ring true for herding induced by the U.S. and South African market returns (Guney et al., 2017). This indicates that the domestic market of the frontier markets is not significantly influenced by non-domestic factors and demonstrate the low levels of integration of frontier markets within the global financial system (Guney et al, 2017).

Chang et al, (2000) embarked on a study that examined the behaviour of investors across different international markets in, South Korea, Taiwan, Hong Kong, the U.S. and Japan. The investigation was studying the tendency of these investors to exhibit herding behaviour among different asset classes. The investigation used the CSSD model to detect herd behaviour in the markets and the CSAD model to the measure dispersion. The study collected stock price data of all U.S. firms on the NYSE and AMEX, the equally weighted market index and the year-end market capitalizations from the Center for Research in Securities Prices (CRSP) (Chang et al, 2000). The data was collected between January 1963 and December 1997. Daily prices and returns series and year-end market capitalization of firms and their equally weighted index returns in Hong Kong between January 1981 and December 1995. In Japan between January 1976 and December 1995, South Korea between January 1978 and December 1995, and Taiwan between January 1976 and December 1995. The data was acquired through the Pacific-Basin Capital Markets Research Center.

The study found no evidence of herding behaviour in the Hong Kong and U.S. markets, there were fragments of herding behaviour in the Japanese market. It was found that the two emerging markets, South Korea and Taiwan, exhibited significant herding behaviour Chang et al, (2000). The study found that during times of extreme price variations Japan, Hong Kong and the U.S. equity return dispersions increase rather than decrease in that situation (Chang et al, 2000).This reinforces the initial results that found no evidence of herding behaviour in the U.S., Japan and Hong Kong markets, and consistent with results by Christie and Huang (1995) regarding the U.S. markets.

Taiwan and South Korea have evidence of herding behaviour, there was evidence of equity return dispersions during extreme up and down price variation periods, Chang et al, (2000). Taiwan and South Korea are emerging markets that are susceptible to macroeconomic announcements and information which play an important role on market participants and their decision making. Thus, macroeconomic data instead of firm-specific data “have a more significant impact on investor behaviour in markets which exhibit herding” (Chang et al, 2000, pp 3).

Fang et al, (2017) analysed the herding behaviour in the U.S. stock market, the study looked at the behaviour of equity fund managers and the impact thereof. The study examined the dynamic herding behaviour of U.S. equity fund managers during different states of the markets. The U.S. mutual fund is one of the oldest funds in the world, it is said to be over 70 years old and represents about 50% of the world’s mutual fund market (Fang et al, 2017). Thus play a very dominant role in the global stock market. The herd behaviour by U.S. equity fund managers may lead to price distortions and price fluctuations in the global markets but this herd behaviour may also be informational for subsequent fund returns (Fang et al, 2017). The study measures positive and negative herding, the different effects herding has on different types of equity funds, tests for asymmetries in herd behaviour contingent on market circumstances, fund size and the age of the fund (Fang et al, 2017). Lastly, the study investigates how herding by U.S. equity fund managers impact prices in the global stock market and analyse the returns of the funds herding effects to monitor their post-herding performance (Fang et al, 2017).

The investigation makes use of a regime-switching-based CSAD model to analyse the dynamic nature of the herding behaviour of U.S. fund managers of equity-type funds in the global stock markets. Unlike the traditional LSV model, which is set in an efficient market, the CSAD model is based on the CAPM model of returns and time variance (Fang et al, 2017).

Monthly data from 3033 U.S. equity funds was used for the investigation over a period of 12 years from January 2001 to December 2013 from CRSP (Fang et al, 2017). The types of funds investigated in the study included: aggressive growth funds, growth funds, value funds, small stock funds, emerging market funds and international funds (Fang et al, 2017).

The results of study show no evidence of herding behaviour by U.S. fund managers using the static CSAD model, however, when the dynamic Markov-regime switching CSAD model was used it confirmed the dynamic nature of fund herding contingent on the co-movement between individual fund return dispersions and market returns (Fang et al, 2017).The study also found a stronger negative herding behaviour for different types of funds during an expansionary period, whereas there is more significant evidence of positive herding for these types of funds during a recessionary period (Fang et al, 2017). The study also indicated that herd behaviour by U.S. fund managers is informational during an expansionary period that when the market is in a recessionary period. The impact of this type of herding by U.S. fund managers on informational values appears within six months of the herding behaviour (Fang et al, 2017). The post-herding returns achieved are reversed within the next year (Fang et al, 2017).

A study by Benkraiem et al, (2019), provides evidence on the herding behaviour on public listed SMEs in the UK and France. SMEs all over the world form part of the backbone of their economies, the growth and success of these SMEs depends on their capability to source external funding which is of great importance for investors and society at large (Benkraiem et al, 2019). According to Benkraiem et al (2019), there has been some academic neglect with regards to the behaviour of listed SMEs. The study intends to provide evidence of herding behaviour of publicly listed SMEs by looking at micro-cap stocks which are listed SME indices that make up the equity market sector which little is known about the propensity of investors to herd compared to the large, listed indicators in Benkraiem et al, (2019). The study aims to detect herding behaviour in a highly specialized market and its differences or similarities to that of large cap markets. It has been shown that herd behaviour may exhibit itself unequal across firms of different sizes, small firms are associated with high levels of herding, it is expected that SMEs will display high levels of herding compared to large firms due to the larger asymmetries faced by SMEs.

The investigation looked at herding of four equity markets for a period of 11 years between September 2005 and December 2016 with data collected from the UK FTSE 100 and FTSE AIM 100 equity indices, and a period 10 years between May 2006 and December 2016 for data collected from the CAC 40 and Alternext All Shares stock indices. The CSAD model is used to evaluate herding behaviour.

Herding was detected in the French and UK micro-capitalization indices during bullish and bearish periods of the market periods. There was no significant herding during the 2008 global financial crisis in both markets. This may have been due to informational asymmetries because investors and funders are of the view that the SMEs do not have informational advantage compared to the larger firms (Benkraiem et al, 2019). This finding correlates with studies on smaller stock markets which display greater herding than the larger stock markets. The study also indicated that herding behaviour is positively correlated with medium and high levels of liquidity which is consistent with a study by Galariotis et al, (2016). However, the CAC 40 index displayed significant herding at high liquidity levels and herding is reinforced at medium liquidity for the French SME index (Benkraiem et al, 2019). Equity fund managers exhibit rational herding in SMEs and irrational herding in large firms, this provides diversification potential for SMEs (Benkraiem et al, 2019).

Market breadth is a measure of the difference between the average number of rising stocks and the average number of falling stocks within a market or an industry (Zaremba et al, 2020). Furthermore, market breadth is used as a proxy for herding behaviour in the study. Zaremba et al, (2020) investigated the role of market breadth on asset prices in global equity markets, the study assessed if the correlated trading has predictive ability for future stock performance.

The study sample consisted of country and industry portfolios from 64 markets from 1973 to 2019 Zaremba et al, (2020). High market breadth countries and industries surpass the performance of countries and industries with low market breadth, thus markets with significant herding perform better than markets with low herding behaviour. These effects are also contingent to the size, style, volatility, skewness, momentum, and trend-following signals of the firms in the market (Zaremba et al, 2020). Furthermore, the market breadth effect is distinctly prominent in markets with high limits to arbitrage, following bullish periods, and in collectivistic societies, supporting behavioural explanations of the phenomenon.

Future studies on the subject matter may extend the analysis in two aspects: 1) an investigation into the fund flows linked with the herding effect. For instance, is the effect of an intra-country phenomenon driven by local investors or an international phenomenon driven by global fund flows? 2) an investigation into whether the effect present in asset classes, other than equities, such as corporate bonds, listed property or commodity futures (Zaremba et al, 2020).

Gabbori et al (2020) seek to examine herding in the Saudi Arabian equities market by answering the following questions: firstly, does the oil market volatility impact herding behaviour in the Saudi equities market and secondly, does announcements from the cyclic OPEC meetings impact herd behaviour.

The price of equities tends to be distorted due to herding, the increase in volatility impacts risk averse investors from going into the market (Gabbori et al, 2020). In developing equity markets this type of behaviour by investors may destabilize the financial market, discourage investors, imply market manipulation, and reflect badly on overall market functioning and integrity. Galariotis et al, (2015) suggest that herd behaviour and/or volatility in one market may be prompted by trading transactions or information from different but related financial markets. Herding behaviour in a particular financial market may be triggered by trading activity and/or information originating from other related markets. Klein (2013) supplemented the study and indicated that the transmission can be bidirectional between the two related market which were the U.S. and European equity markets. Galariotis et al, (2016) found that herding in the UK equity market may be triggered by volatility in the U.S. equity market and Klein (2013) found that volatility in the UK equity market triggered herding in the U.S. equity markets. This has significant consequence for global hedging and fund diversification (Gabbori et al, 2020).

The Saudi Arabian economy is highly dependent on its oil market, thus volatility in the oil market may have an impact on the herding behaviour of the Saudi equities market (Gabbori et al, 2020). Saudi Arabia is one of the largest oil producers in the world and produces 13% of oil demand and has 22% of the world's oil reserves. Due to the substantial market capitalization information transmission occurs between the equities market and changes in the oil price. Saudi Arabia is an emerging market and thus is expected to be informationally inefficient and prone to herding behaviour (Gabbori et al, 2020.)

There is a narrow gap that lies between the supply and demand of oil which makes the oil market sensitive to announcements about international oil consumption and production and oil prices oscillate during short periods of time. In recent times, OPEC meetings have become contributors to the oscillating oil prices. Oil demand is dependent on global economic growth. The U.S. and Western Europe used to be the main source of demand for oil, but both the U.S. and Europe have had a decline in economic growth (Gabbori et al, 2020). In recent years the demand for oil emanates from emerging countries such as India, the Middle East and China which are growing relatively higher than the developed economies (Gabbori et al, 2020).

Empirical studies have elucidated the transmission from the oil to the equities markets, however, no study has focused on oil volatility and OPEC announcements impact herding behaviour in these markets (Gabbori et al, 2020). The oil market variations are news for domestic equity market investors in oil producing countries. Increases in the oil price tend to kick-start the business cycle with significant implications on equity prices and returns. Thus, it is vital to study whether announcements and fickleness of the oil market can institute herding in the equities market in oil producing country (Gabbori et al, 2020).

The investigation regressed the CSAD of returns on absolute and squared market returns, data was collected from listed companies in the Saudi market between January 2005 and the September 2019, a total of 175 companies formed part of the sample.

The investigation revealed that there is herding in the Saudi equity market, the study was shown to be independent of the oil market volatility (Gabbori et al, 2020). It was found that herding behaviour was present during the OPEC meetings periods; however, only when there is high global uncertainty such as the global financial crisis. Herding behaviour was also found post the global financial crisis; however, herding was absent in the Saudi equity market during bullish market conditions (Gabbori et al, 2020).

3.2.3 Real Estate

Bertin et al (2005) analysed the liquidity difference between REITs and common stocks. The authors start the study stating that REITs are required to pay out at least 90% of as dividends as unitholders, it implies financial liquidity remains a challenge for REITs. Moreover, the authors envisage that requirement for amount paid out as dividends, decreases information asymmetry in REITs. Ke and Sieracki (2019) found contradicting finding-information asymmetry tends to be high in REITs Bertin et al (2005) argue that (il)liquidity in terms of information transfer has the following implications. First, the liquidity has minimization effects and second, the liquidity in REITs might imply that their traits are similar to common stocks. In terms of trading patterns, Bertin et al (2005) argue that informed and discretionary traders prefer to take into account information when trading for liquidity reasons. At the same time, traders will account for opening and closing trading times. In order to determine liquidity, their study hinges on friction and friction. Based on prior economic heuristics, the authors opine that higher variance should imply low liquidity. The data is on trades and quotes (TAQ) from the NYSE. Parameters pulled out of the TAQ include time-stamped trade prices, trade sizes, and bid-ask and depths. The non-REITs and REIT for the entire 1996 year. They used a multilinear regression to detect herding behaviour.

The results of Bertin et al (2005) illustrate bid-ask spread, as percentage, is larger in non-REIT stocks than in REIT stocks. Furthermore, percentage is higher during the morning and decreases as one moves to the afternoon. In terms of pattern, common stocks and REITs have J-shape and U-shape, respectively. According to Behrendt and Schmidt (2018), U-shapes offer more strategic opportunities than J-Shapes. Womack (2012) stated that REIT corporate activities, predominantly take place for strategic reasons. Further analysis shows that in the intraday variance is higher REITs than common stocks. That would imply that REIT intraday investors herd towards the direction of non-REITs. The salient findings from Bertin et al (2005) are as follows. First, variance tends to be higher in common stocks than in REITs for most part of the day. Second, fiction is more in common stocks than in REITs. That would imply investors herd in common stocks. Third, the U-shapes for most part of the day are similar in common stocks and REITs. That would imply that common stocks and REITs offer the same investment benefits. Fourth, price measure and return measure are higher for REITs than common stocks. Fifth, macro-economic variables have more influence in REITs than non-REIT stocks. Fundamentally, the investors tend to herd into liquid investments such as common stocks than to illiquid REITs.

Hatemi-J and Roca (2011) studied how contagious was the U.S. real estate market during the subprime crisis (2007/2008). The authors stated that during subprime crises, the spillovers, by extension the herding-in and-out behaviour is much higher. Then, the questions why and this is the main answer is in that Hatemi-J and Roca (2011). While in the relation to the former statement, similar patterns are evident during distress periods. Fundamentally, Hatemi-J and Roca (2011) stated that during crises, some assets gain more in value while other assets loose value. Among other factors that have, increased financial integration is globalisation. That has led to some countries caught off in terms of handling financialisation of their markets due to globalization. To test herding in principle, they used multiple regression, matrixes and pairwise bootstrap approach. The data is on the U.S., Australian, Japanese and the UK real estate markets.

The results of Hatemi-J and Roca (2011) illustrated that it is only after summer of 2007, when the world experience a full-blown crisis. They chose the structural break point as August the 1st, 2007. According to Hatemi-J and Roca (2011), rating agencies started issue warning about mortgage-backed securities (MBS) and collateralised debt obligations (CDOs) as from spring of 2007. During that period, liquidity evaporated, and credit markets shorten their papers without investigating how much is backed by subprime mortgages. Broadly, the results illustrated that the four markets are interdependent with one another. That is, investors, herd-in and-out of those markets without evident patterns. That might be probably that everyone was searching for a safe market for investments. Put it differently, during subprime crises herd in-and-out of real estate markets in an unsystematic manner.

Kallberg et al (2014) studied co-movements of Case-Shiller price indices for fourteen metropolitan areas during the period of 1992 to 2008. The Case-Shiller index is a repeated sales housing price index. At the heart of their study, it is investigating the co-formation of U.S. residential real estate market prices. Kallberg et al (2014) focused on (i) excess covariation and (ii) the degree of excess correlation in financial contagion. The monthly data returns used in the study by both authors is between January 1987 and December 2008. The metropolitan areas covered in Kallberg et al (2014) are Los Angeles, San Diego, San Francisco, Denver, Washington (DC), Miami, Tampa (FL), Chicago, Boston, Charlotte (NC), Las Vegas, New York, Cleveland (OH) and Portland (OR). A multi-factor model used to explore prices co-movements of residential houses. In order to omit misinformation, Kallberg et al (2014) included the time series returns for the composite and S&P500 as proxies, (i) systematic real estate risk and (ii) stock market risk, respectively. Furthermore, they tested for fundamental and excess co-movements of housing prices and for that, they used latent co-movement vector. And ordinary least squares (OLS) were used for excess and raw co-movements.

The fitted graphs in Kallberg et al (2014) show that prices co-movements, especially as from the late 1990s are high. The authors opine that that pattern of prices co-movements is evident on local and national level. The prices co-movements were more evident in raw houses. The listed systematic factors had explanatory power of at least 80% since 1997. The dynamic co-movements of housing prices were intertwined for most part of the sample period. That is, if prices for one metropolitan area increases (decreases), so are other metropolitan areas. One reason for that might be the fact that the analysis metros are mainly suburban areas in one country. The robustness tests-based OLS, Ljung-Box test, fifth-order serial correlation and Lagrange multiplier statistic confirmed the earlier findings. Kallberg et al (2014) did further analysis, explored different prices regimes. Fundamentally, prices changed to a different regime when they hit a certain structural break point. The latter phenomenon is termed ripple effect by Balcilar et al (2013). Surprisingly, (i) raw CSI return movement, (ii) real estate momentum and (iii) stock market momentum plays a less role in prices co-movements of the U.S. residential property market. This could be to the fact that, during 1992-2008 period, the U.S. residential property market was stable. The subprime crisis started in 2007-2008 period.

Babalos et al (2015) disentangled different herding behaviour of the U.S. REITs based on different regimes. In order to capture different regimes, they used Markov-regime switching model. Babalos et al (2015) ascertain those bubbles of asset prices emanating from herding conduct of institutional investors. They put forward the Markov-regime switching model because the model has ability to capture nonlinear movements. For their analysis, they started with accounting for dispersion of returns using the CSAD approach. The data covers from 2004 to 2013 period and is made of the U.S. REITs listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and Nasdaq Stock Market (Nasdaq). Intuitively, according to Babalos et al (2015), when there is not herding behaviour, the coefficient in the model should be statistically insignificant. The results illustrate that there is substantial evidence supporting regime-dependent variance. According to the authors, those results confirm existence of three regimes for these U.S. REITS stock returns. What is unique about the regimes, they capture the herding behaviour (Babalos et al, 2015). Interestingly, the authors define negative herding as anti-herding behaviour for all REITs for the two regimes in the Markov-regime switching model. The two rectors' sectors that did not show any signs of herding behaviour is industrial and office sector. Those findings are surprising because office sector in the U.S. has been volatile sector while industrial tends to be tranquil (See, Marcato et al, 2019).

Huang et al (2016) studied time-varying co-movement between REITs and stocks during the 2000-2014 period. Huang et al (2016) state that between 2007 and 2008, most stock market parameters lost value-real estate house price index by 20% and S&P500 dropped 50% of its value. The authors opine that REITs are important when one considers diversifying in a portfolio. The data is from January 3, 2000 to December 31, 2014 made up of logarithmic weekly prices returns made up of 783 observations. In order to tests those co-movements, Huang et al (2016) copula function, marginal distributions and the symmetrized Joe-Clayton copula function. Further analysis includes testing range-based volatility model. For that, the author used the asymmetric conditional autoregressive range. For the economic evaluation, they use constant relative risk aversion utility function.

The empirical results from Huang et al (2016) reveal that volatility patterns are more sensitive in the short-run than in the long-run period. The leverage effect parameter is positive and statistically significant-according to the authors that shows that co-movements are evident and herding behaviour is present among REITs and stocks. Moreover, more information is captured in the long-run than in the short-run. The volatilities are more volatile during 2008-2009 than any other period. This is because 2007/2008 was the period of subprime crisis. The volatility models captured most of the volatilities during the volatile period, especially the asymmetric conditional autoregressive range model. The fact that volatility co-movements were non-directional, Huang et al (2016) argue that in asset allocation, volatility modelling needs an integrated approach. Furthermore, range-based modelling offered superior outcomes than return-based framework.

Blau et al (2016) examined differences in delayed prices of REITs and non-REITs. According to the authors, prior studies shave suggested that those differences are due to; (i) purchasing costs and (ii) adverse selection problem. At the heart of Blau et al (2016) the prices delay of equity REITs. It can be inferred from prior studies that the performance of the equity REITs mimics the performance of common stocks-Mori and Ziobrowski (2011). Furthermore, REITs increase market frictions than common (Blau et al, 2016, and Mori and Ziobrowski, 2011). The data used in Blau et al, (2016) is based on monthly trade publications collected from the National Association of Real Estate Investment Trusts (NAREIT). The tests done to verify the presence market fiction include (i) differences in price delay across REIT and non-REIT stocks, for that they used matching procedure by prior empirical studies, (ii) Wednesday effect, common known as Wednesday-to-Wednesday returns, they test using multilinear regression, and (iii) price delay effect, multilinear regression was used for this test. Parameters insert included market capitalization, idiosyncratic volatility, weekly equity reruns measured by CAPM, outstanding shares held by institutions, (il)liquidity measured by the number of traded shares, volume of trade shares and number of days that the stock traded in a year.

The results of Blau et al (2016) illustrate that REITs had significantly less shareholding and employees than non-REITs. The results are not surprising because by law REITs should have a certain number of shareholders, appropriately called unitholders (Mühlhofer, 2019). Further analysis shows that there is a positive price delay with REIT ($\rho = 0.041$). According to Blau et al (2016), the delay in prices is most likely to be mispriced by the market. Moreover, the results confirmed that it takes longer for information to be incorporated into prices of REITs. According to Marcato et al (2019), the absorption of information into the prices of REITs is subjected to lagging effect. Blau et al (2016) went further tested which parameters explained most of the variation in prices. For that, they used principal component analysis. The analysis from the PCA confirmed the major contributor to the delay of information absorption is the idiosyncratic risk. On the other hand, the low turner in stocks led to lower volatility. That is consistent with microstructure studies. On what drives greater delay in REITs, based on difference-in-difference OLS, Blau et al (2016) confirmed that major delays are due to; (i) idiosyncratic risk, (ii) market risk and (iii) number of traded days. Remember that the CAPM incorporates market risk as one of its parameters; hence, equity returns contributes to greater delay incorporation of information into prices of REITs. On the specific REITs traits that influence delays, the authors found that; (i) larger REITs with lower idiosyncratic risk and (ii) reduced book-to-market ratios reduce price delays.

Freybote and Seagraves (2017) put forward that commercial real estate investors differ from other real estate investors because of; (i) sentimental market expertise, (ii) investment strategies and (iii) future conditions. That is, at the heart of Freybote and Seagraves (2017), it is about finding out about the heterogeneous sentiments among commercial real estate investors. They opine that commercial real estate investments are unique because of heterogeneous properties, variable cyclical liquidity, arbitrage opportunities and efficiency of information. Freybote and Seagraves (2017) use the Real Capital Analytics quarterly investments and divestments data for; (i) institutional investors (i.e. banks, insurance companies and pension funds), (ii) publicly listed REITs and (iii) privately held companies (those firms focus on investing, developing and operating commercial properties) during the period of 2001-2014. And each transaction should be at least be worth $2.5 million. For the analysis, the authors started by calculating the buy-sell imbalance (BSI) formula, taken from Kumar and Lee (2006). According to Freybote and Seagraves (2017), $BSI > 0$ illustrates positive sentiment (optimism), by extension herding behaviour while $BSI < 0$ shows negative sentiment (pessimism). To control different sentiments based on office type, they used exogenous variables (macro-economic, capital market and property market fundamentals) in the bivariate VAR model. To control for investing tendencies of institutional investors, they included the total NAREIT return for office REITs (Freybote and Seagraves, 2017). To control market performance, they used S&P500 index, and Chicago Board Options Exchange (CBOE) volatility index to control general market sentiments.

The results Freybote and Seagraves (2017) showed that institutional and sentiments of investors were positive for REITs except for offices during the period of 2001-2014. That is, there was herding behaviour in REITs. Moreover, volatility changes were larger for institutional and private investors. That is, institutional and private investors, set-up trends in terms of investing behaviour. For all office (including CDB offices), institutional and REITs, sentiments exhibit negative autocorrelation. According to the authors, that implies those investors source information for investing. That is, they are trend followers not trendsetters. Those changes in REITs move in tandem over time. When results are lagged from the first lag up to the fifth one, emerging patterns are similar throughout the time series.

Ke and Sieracki (2019) investigated sentimental trading behaviour among London office market investors. They focused on four types of investors; (i) UK institutional investors, (ii) UK private investors, (iii) UK listed real estate/REITs and (iv) overseas investors. The authors opine that investor behaviour among different investors tend to be driven by noise of traders-sometimes called white noise. According to Ke and Sieracki (2019), sentimental information used in conjunction with market fundamentals. The modelled herd behaviour using the VAR, lagged from the first to the fifth lag. The lagging issue is important for the real estate markets as information in prices of properties is lagged (See; Kola, 2021). The authors stated that in the context of herd behaviour, proper analysis should show past losers and past winners. The latter pattern is contrarian investment behaviour (Ke and Sieracki, 2019). This study hopes to reveal the contrarian investment behaviour.

The data used by Ke and Sieracki (2019) is on Central London office transactions from Property Archive and included commercial properties worth at least £1 million. The investors are defined as being local (i.e. British) except when the source of money comes outside UK. In a case like that, investors are defined as being overseas. In total, 4473 effective transactions made the sample of their study. For the modelling, Ke and Sieracki (2019) used a quarterly sentiment buy-sell imbalance index and the unrestricted VAR model. The preliminary results of Ke and Sieracki (2019) illustrate that the sentiments of the UK sentimental and listed real estate investors are -0.21 and -0.27, respectively. That would imply less herding behaviour on the side of the UK sentimental and listed real estate investors when investing in the London office market. The VAR results show that institutional investors, private investors, public real estate investors and overseas investors herd in-and-out when investing, especially in the early years of investments. That might be because one in early investment stages is trying to find the direction of investments. Secondly, London office market has always been an attractive first for a long period up until the 2007/2008 subprime crisis. Furthermore, overseas and public real estate investors hardly influenced the UK institutional investors. However, overseas investors influence British investors. All those patterns were evident from the first lag all the way to the fifth one. Fundamentally, Ke and Sieracki (2019) argued that herding behaviour is influenced by spillovers among different Central London office market investors.

In order to strengthen their results, Ke and Sieracki (2019) performed the same analysis on the stock market as illustrated by the FTSE250. The results of the FTSE250 show that its returns are negative and statistically significant. According to Ke and Sieracki (2019), that illustrates that the institutional investors allocate more investments to real estate than any other asset class. That might be probably to the fact that diversification benefits are inherent in real estate assets. Broadly, overseas investors invest in the Central London office market because that market has been attractive property investment. On the other hand, sentimental information is an additional driver of co-movement of assets (Ke and Sieracki, 2019).

Kola (2021) studied volatility interconnectedness among volatility of bonds, commodities, equities and real estate indices in Brazil, Russia, India, China and South Africa countries. This study is different from Kola (2021) because; first, it focuses on different geographies and second, it focuses on indices returns instead of volatilities. The authors opine that nation offered a unique laboratory because those financial markets of those nations are underpinned by, political environment, drivers of economic policy and governance structures. For their study, Kola (2021) used weekly logarithmic data from the BRICS countries starting from January 2007 to December 2017. They divided their data into; (i) out-sample (2007) for forecasting performance and (ii) in-sample (2012 to 2017) for estimating parameters. They used the following indices. Firstly, Brazil-Brazilian IBRX 50 for equities, IMOB for real estate, BM&F BOVESPA for commodities and Brazil 87/8 04/15/24 bond index, (ii) Russia-Moex index for equities, created a real estate based on PIKK Group, PJSC LSR Group, world trade centre ordinary shares and world trade centre preferred shares because Russia does not have a real estate index, MICEX and Gas index for commodities and RFLB08/29/18 bond index, (iii) India-Nifty 50 for equities, Nifty Realty for real estate, Nifty commodities index and Nifty 10yr bond index, (iv) China-SSE50 for equities, SHROP real estate index, CCI for commodities and GT USDDCN 15yr bond index, and (v) South Africa-JSE Top 40 for equities, all property index (J803), JCGMSAG mining index and SA $10^1/_2$12/26 bond index.

The preliminary results of Kola (2021) illustrate that there are spikes in all four indices, which might be due to spillovers. This is because basics statistics (i.e. mean, minimum, maximum, standard deviation, kurtosis, skewness and Jarque-Bera test) confirmed that the data is skewed into different directions. They modelled spills using Cholesky decomposition, VAR and Markov-regime switching models. The out-sample results from the Cholesky decomposition show that spills are statistically significant between and in between the following countries. For bonds; (i) from Brazil into Brazil, from (ii) India into India and from (iii) Brazil into South Africa. For commodities; (i) from Brazil into Brazil, (ii) from China into Brazil, (iii) from China into China. In equities markets; (i) from Brazil into Brazil, (ii) from India into China, (iii) from Brazil into Russia and (iv) from India into South Africa. Last, for real estate markets; (i) from China into Brazil, (ii) from India into China, (iii) Russia into Indian and (iv) from Russia into Russia. The in-sample results illustrate similar findings to out-sample findings. Kola (2021) argued that fact that out-sample results mirror the in-sample; first, it illustrates the quality of the data and second, it shows the robustness of the results. In terms of Markov-regime findings, the results move between and in-between different countries without any specific pattern. Put it differently, when the parameter is the country or index, be between or in between parameters, the movements are indiscriminately. The regimes based on indices are similar to the latter statement. Interestingly in certain situations, illiquid indices (i.e. real estate) converge and change regimes much quicker than liquid indices (i.e. commodities and equities). The author argue that might be because securitised real estate markets are becoming increasingly integrated into other capital markets instruments.

Bouri et al (2020) studied nonlinear transmission between stocks and real estate markets using Gaussian correlation approach. The Gaussian correlation approach is a stochastic process in which random variables have multivariate normal distribution. Moreover, those random variables have joint distributions among themselves. The reason why they used Gaussian correlation approach is because it avoids biasness of conditional correlation, and it captures nonlinearity of structures. For further analysis, they focused on marginal in the markets. And for that, they use Generalised Autoregressive Conditional Heteroskedsticity (GARCH, here after)-family models. The reason why GARCH-family models are used it is because they capture volatilities dynamism. To validate their results, they created a bootstrap test for contagion. The analysed period is from January 1, 1998 to September 13, 2018. The data is on REITs and equity markets of 19 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Ireland, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Singapore, South Africa, Spain, Turkey, UK and U.S.). The data is on the selected Morgan Stanley Capital International indices of those selected countries. In order to avoid biasness due to exchange control, every index is quoted in American dollars. Just like other studies (Blau et al, 2016 and Kola, 2021); they highlight the issue of illiquidity when investing in real estate assets.

The results of Bouri et al (2020) are sup-divided into the following groups. First, cross-market: contagion between REITs and equity, and then, cross-country: contagion between U.S. REITs and REITs of other countries, and finally, cross-market-cross-country: contagion between U.S. REITs and equity of other countries. The reason for structuring results in the manner for the last two sub-groups is that the U.S. has the biggest capital market in the world. For the first sub-set of results, one sees that the European debt crisis and the Brexit has more impact in the U.S. than in the same country. Moreover, the local Gaussian correlation decrease over time. That would imply that investors were herding out of EU markets. During the same period, in the U.S., REITs were mainly investing in commercial real estate, except for mortgage REITs. On the other hand, the results showed no transmission into the UK after the Brexit vote. Bouri et al (2020) argue that the latter finding may illustrate those negotiations have not been as fruitful as yet.

For the second sub-set, the results reveal that cross-country linkage with the U.S. REIT market because of the U.S. dominance. That is, investors were herding into the U.S. REIT market. Given that at 95% of the U.S. REIT firms are specialised, diversification benefits were evident especially in the U.S. REIT market. That might explain why other markets were herding into the U.S. REIT market. On the last section of the results, Bouri et al (2020) illustrate that transmission from the U.S. REITs to equity markets is high for most countries-week effects in France, Germany, Italy and Singapore, except for New Zealand, Hong Kong, Japan and Malaysia. For EU countries (weak effects for Netherlands and high effects for Ireland, the UK and Italy), transmission in their equity markets with the U.S. REIT market during the EU debt crisis. That is, EU investors were herding into the U.S. REITs during the EU subprime crisis.

Fundamentally, the nonlinear transmission is evident between equities and REITs markets across the entire sample and that requires portfolio rebalancing especially during bad times.

3.2.4 Conclusion

Numerous studies have shown the interconnectedness between financial, commodity and real estate markets (Chan, Treepongkaruna, Brooks and Gray, 2011; Liow and Ye, 2018) A solid grasp of the interconnections between various asset types is crucial when constructing investment portfolios (Chan, Treepongkaruna, Brooks and Gray, 2011; Liow and Ye, 2018) and for policymakers need to examine the channels through which volatility is transmitted and address potential contagion between real estate and other financial markets (Liow and Ye, 2018).

There is evidence that the relationships between returns across different assets tend to shift during times of market stress. There is evidence of market contagion and shifts in investor preferences between asset types. In calmer periods, marked by lower volatility and notably positive stock returns, a flight away from safe assets, such as gold, towards stocks is observed. In contrast, during crisis periods with heightened volatility and steep declines in stock prices, contagion between stocks, oil, and real estate becomes evident. Additionally, these times see a pronounced flight to quality, where investors move from stocks to Treasury bond. Liow and Ye (2018) showed that during periods of high volatility in SRE markets, stock market returns and changes in foreign exchange rates have a stronger positive impact on SRE market returns. Also, stock and bond market risks are negatively linked to SRE market risk, suggesting potential hedging opportunities (Liow and Ye, 2018). The spillovers between housing, stock, and bond returns are typically limited, with shocks in the stock and bond markets having a greater influence on housing returns than the reverse (Tiwari, André and Gupta, 2020). The interactions between REITs and stocks are notably stronger in both directions compared to those between REITs and housing (Tiwari, André and Gupta, 2020). Housing market shocks, particularly after the subprime crisis, tend to have the most enduring effects, indicating a prolonged economic impact (Tiwari, André and Gupta, 2020).

The interconnectedness between financial, commodity, and real estate markets is well-documented, with numerous studies highlighting the importance of understanding these linkages for both investors and policymakers (Chan, Treepongkaruna, Brooks and Gray, 2011; Liow and Ye, 2018; Tiwari, André and Gupta, 2020). During periods of market calm, there is a tendency for investors to move from safe assets like gold to riskier assets such as stocks, whereas times of heightened volatility led to contagion between markets and a shift to safer investments like Treasury bonds. Evidence shows that shocks in the stock and bond markets have a more significant impact on housing returns than the reverse, with the relationship between REITs and stocks being particularly strong in both directions. Moreover, housing market shocks, especially following the subprime crisis, have persistent and long-lasting effects on the economy. The volatility transmission channels between these markets suggest potential hedging opportunities, especially in real estate equities (SRE), where stock market returns, and exchange rate changes significantly influence market behavior.

This conclusion is crucial in a herding study because it highlights the dynamic relationships between asset classes, particularly during periods of market stress, which are often associated with herding behavior. The evidence of contagion between stocks, oil, and real estate during crises and the flight to safer assets like Treasury bonds underscores the potential for herding in these markets. Understanding the spillovers and volatility transmission channels is essential for identifying how herding can amplify market shocks and spread risk across asset classes. Additionally, the persistence of housing market shocks and the stronger link between REITs and stocks point to areas where herding may have more significant and prolonged impacts, which is vital for developing strategies to mitigate systemic risks in financial markets.

Analyzing herding across equities, bonds and listed real estate can reveal potential spillover effects. For example, herding behavior in the equity market could spill over into the bond and real estate markets, especially during periods of financial uncertainty (Balcilar et al., 2013). Understanding these interactions is essential for portfolio diversification and risk management. The findings of this thesis are expected to provide critical insights by addressing gaps in the literature, particularly in understanding the role of herding behavior in emerging and developed markets, the influence of market conditions (e.g., volatility), and the potential for herding spillovers across asset classes. Most herding studies have focused on individual markets (equities or bonds) or specific regions, but this research expands the scope to a comparative analysis across multiple asset classes and geographic regions (Chang et al., 2000; Demirer et al., 2019). By better understanding herding behavior, this research can help regulators design policies to minimize the risks associated with market bubbles and crashes. For instance, better-informed regulations could be developed to mitigate irrational market behavior, thus fostering greater market stability and investor confidence (Choi & Skiba, 2015).

The findings on herding of these asset classes have implications for portfolio diversification, asset allocation, and policy management, particularly during periods of financial stress

3.3 Modelling

At the heart of this study is illustrating market-herding behaviour of among the three market indices (i.e. bonds, equities and REITs) of the selected countries (South Africa, Taiwan, UK and U.S.). In doing the analysis, one wants to see which parameter leads the herding behaviour. And, one factor which is suitable for that is PCA. The advantage of PCA according to Kola and Kodongo (2017) is that it extracts the major contributing factor to a causal effect. In presenting PCA, one assumes that data is a matrix x, where rows are objects and columns are variables, then;

$$\boldsymbol{x}^T\boldsymbol{x} = n\boldsymbol{v} \tag{3.1}$$

where $\boldsymbol{v}$ is the covariance matrix of data.

The most widely acceptable model is illustrating herding behaviour is the VAR model. Kola (2021) illustrated that the VAR can capture in between and across herding behaviour of volatilities. And, by extension interrelationship between variables. This study adopts the VAR model as illustrated in Kola (2021). The general VAR formula is;

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \mathrm{e}_t \tag{3.2}$$

where the l-periods back observation y_{t-1} is called the l-th lag of l-th lag of y, c is a $k * 1$ vector of constants (intercepts), A_j is the time-invariant $k * k$ matrix and e_t is a $k * 1$ vector of error terms satisfying $\mathrm{E}(\mathrm{e}_t) = 0$, every error term has mean zero. $\mathrm{E}(\mathrm{e}_t \mathrm{e}_t') = \Omega$, the contemporaneous covariance matrix of error terms is Ω (a $k * k$ positive-semidefinite matrix. $\mathrm{E}(\mathrm{e}_t \mathrm{e}_{t-k}') = 0$, for any non-zero k, there is no correlation across time; in particular, no serial correlation in individual error terms. In order to have deeper understanding of market herding, there will be lags in the VAR model. Ke and Sieracki (2019) illustrate that herding behaviour changes patterns with the number of lags one has, in particular in the real estate industry. Given that this study includes real estate indices from different countries, lagging of results is most likely to reveal more findings. Ke and Sieracki (2019) lagged their results up to five lags.

3.4 Data

3.4.1 Preface

An emerging market economy is the economy of a developing nation that is becoming more engaged with global markets as it grows (Crittenden and Crittenden, 2014). Countries classified as emerging market economies are those with some, but not all, of the characteristics of a developed market. As an emerging market economy progresses it typically becomes more integrated with the global economy, as shown by increased liquidity in local debt and equity markets, increased trade volume and foreign direct investment, and the domestic development of modern financial and regulatory institutions (Demirgüç-Kunt and Levine, 1996).

A developed economy is typically characteristic of a developed country with a relatively high level of economic growth and security (Divecha et al, 1992). Standard criteria for evaluating a country's level of development are income per capita or per capita gross domestic product. Moreover, the level of industrialization, the general standard of living, and the amount of technological infrastructure (Landau, 1986). Figure 1 provides a list of countries that have been categorised as frontier, emerging and developed markets.

Figure 3. 1: Frontier, emerging and developed markets

DEVELOPED MARKETS			EMERGING MARKETS			FRONTIER MARKETS			
Americas	Europe & Middle East	Pacific	Americas	Europe, Middle East & Africa	Asia	Europe & CIS	Africa	Middle East	Asia
Canada	Austria	Australia	Argentina	Czech Republic	China	Croatia	Kenya	Bahrain	Bangladesh
United States	Belgium	Hong Kong	Brazil	Egypt	India	Estonia	Mauritius	Jordan	Sri Lanka
	Denmark	Japan	Chile	Greece	Indonesia	Iceland	Morocco	Oman	Vietnam
	Finland	New Zealand	Colombia	Hungary	Korea	Lithuania	Nigeria		
	France	Singapore	Mexico	Kuwait	Malaysia	Kazakhstan	Tunisia		
	Germany		Peru	Poland	Pakistan	Romania	WAEMU		
	Ireland			Qatar	Phillipines	Serbia			
	Israel			Russia	Taiwan	Slovenia			
	Italy			Saudi Arabia	Thailand				
	Netherlands			South Africa					
	Norway			Turkey					
	Portugal			United Arab Emirates					
	Spain								
	Sweden								
	Switzerland								
	United Kingdom								

Source: MSCI (2021)

Developed and emerging economies stock markets have distinct differences and behaviours. There is a low correlation between emerging stock returns and developed markets which presents an opportunity for investors in developed markets to diversify their portfolios and increase the expected return on their portfolio while reducing their risk (Divecha et al, 1992). Modest investment in emerging economies has shown to lead to lower portfolio risk and increased annual returns for international investors (Divecha et al, 1992). Emerging markets have shown high rates of economic growth which provide a myriad of investment opportunities, and the rapid economic growth of emerging stock markets has also garnered attention from academics and policymaker (Kunt and Levine, 1996). The rate of economic growth exhibited by developing countries, it is expected that their growth will exceed the rate of growth in the developed markets. Thus, it is expected that long-run stock returns in emerging economies will surpass that of developed markets (Divecha et al, 1992).

Stock market firms in emerging economies have exhibited less distinction between ownership and management compared to firms in developed markets (Bao and Lewellyn, 2017). Firms in emerging markets faces issues of conflict of interest between controlling shareholders and minority shareholders (Bao and Lewellyn, 2017). The boards of directors in emerging markets are not actively involved in monitoring corporate executives as seen in developed markets; rather, it is the firm owners who largely fulfil the governance role of monitoring (Bao and Lewellyn, 2017). Economies with developed stock markets have also shown to have better banking systems and nonbank financial systems which include finance companies, mutual funds, investment companies, brokerage houses, and pension funds (Kunt and Levine, 1996). On the contrary, economies with weak or developing stock markets tend to have weak financial intermediaries (Kent and Levine, 1996).

Chowdhury, Dungey, Kangogo, Sayeed and Volkov (2019) opines that the UK is identified as a market that receives shocks from the US and distributes them into Asia, acting as a bridge market. Taiwan, as part of the Asia-Pacific region, would likely be influenced by the UK's role in transmitting shocks, either directly or through other intermediary markets such as Hong Kong (Chowdhury e al.,2019). South Africa is found to be a net recipient of volatility spillovers from the U.S. stock market, especially in the post-crisis period (McIver and Kang, 2020). The U.S. market has a stronger influence on the volatility of the South African market than the other way around (McIver and Kang, 2020). Additionally, during times of financial turmoil, the linkages between the two markets become more pronounced (McIver and Kang, 2020).

The South African Real Estate Investment Trusts (SA REITs) market, while relatively small on the global stage, is the most active and capitalized REIT market in Africa, boasting a market capitalization of R193 billion (US$19.35 billion) as of December 2019 (Akinsomi, 2022). Globally, it ranks 21st out of 37 REIT markets listed on the FTSE EPRA NAREIT indices, contributing 0.30% to the index, with a market capitalization of US$4.76 billion as of August 2020 (Akinsomi, 2022). While this positions SA REITs as prominent players within the African continent, their role in the global REIT landscape is modest, especially when compared to dominant markets such as the United States and Australia (Akinsomi, 2022). Despite its smaller size, the SA REIT market presents unique opportunities, including a generally weak correlation with other global REIT markets, making it an attractive option for international investors seeking diversification benefits (Akinsomi, 2022). Empirical studies show that SA REITs exhibit distinct co-movement patterns with other global REIT markets, reflecting their interdependence while not being fully integrated into the global REIT system (Ijasan, Junior, Tweneboah and Adam, 2021).

Notably, the US REIT market tends to lead the South African market, given its dominant share in the global REIT index and its substantial influence on global REIT dynamics (Ijasan et al, 2021). This leadership role underscores the strong interconnection between the US and SA REIT markets, where changes in the US market often influence South Africa’s REIT performance. However, SA REITs take on a leadership role relative to markets like Australia and New Zealand, highlighting their emerging influence in certain regional markets (Ijasan et al, 2021). This partial integration into the global REIT network suggests that South African REITs offer a valuable diversification tool for global portfolios (Ijasan et al, 2021). The evolving nature of SA REITs calls for adaptive policy strategies to manage the changing dynamics between local and international markets. As SA REITs continue to grow and mature, they are poised to play an increasingly significant role within global real estate investment, serving as both an emerging market leader in Africa and a diversifier in international investment portfolios.

The Taiwan REIT market has demonstrated notable growth over the past several years, especially after the global financial crisis (Bao and Li, 2020). By early 2015, the market capitalization of Taiwan REITs reached USD 180 billion, more than tripling from its pre-crisis peak in 2007 (Bao and Li, 2020). This remarkable expansion reflects a strong recovery and underscores Taiwan's emergence as a significant player in the global REIT market. The increase in the number of REITs in Taiwan also points to the market’s robust growth trajectory, supported by rising domestic and international interest in Taiwan's real estate investment sector (Bao and Li, 2020).

In addition to size and growth, Taiwan REITs benefit from the country’s developed financial infrastructure and increasing investor participation. The market's growth has been fuelled not only by domestic demand but also by a surge in foreign investment following the liberalization of trading restrictions on qualified foreign institutional investors in the 2000s (Chen and Demirer, 2018). This increased participation has diversified the market's investor base and contributed to the expansion of Taiwan REITs, solidifying their role within both the regional and global real estate investment landscapes.

Studying both markets is crucial to understanding how emerging REIT markets, like South Africa and Taiwan, integrate into global investment networks, providing diversification opportunities and regional leadership. Insights from these markets can inform adaptive policy strategies and investment approaches, given their evolving roles and growth trajectories.

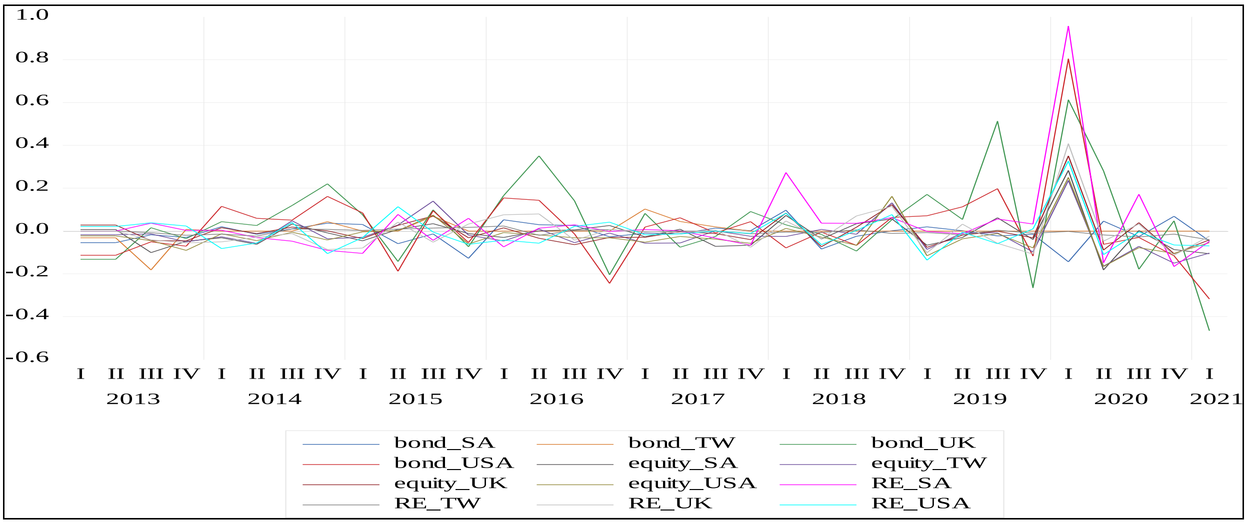
3.4.2 Geographical Focus

The quarterly data of three indices (bonds, equities and listed real estate), starting from 2013 will be on two emerging markets (i.e. South Africa and Taiwan) and two developed markets (i.e. U.S. and UK). The reason for using indices is that they are more encompassing than share prices. In addition, the chosen countries are major players in their respective geographies; moreover, the choice of the countries makes it a global sample. It can be inferred from the use of quarterly data to synchronize stock markets results, especially for boisterous movements such as of equities. On the other hand, Taiwan real estate index is recorded on quarterly basis. The indices used in this study are as follows-the equities indices are; (i) S&P 500 index-U.S., (ii) FTSE all share index-UK, (iii) FTSE/JSE all share index-South Africa and (v) Taiwan stock exchange weighted index-Taiwan. The bonds indices are; (i) the U.S. 30year government bond-U.S., (ii) the UK 30year government bond-UK, (iii) South Africa 30year government bond-South Africa and (iv) Taiwan 30year government bond-Taiwan and listed real estate indices are (v) Bloomberg REIT index-U.S., (vi) FTSE 350 REIT index-UK, (vii) South African listed property index-South Africa and (viii) an aggregated Taiwan REIT index with all the Taiwan REIT indices.

3.4.3 Analysis

3.4.3.1 Background

Figure 3. 2: Index Returns



Note: the x-axis is returns and y-axis is time in quarters. SA is for South Africa, USA for United States of America, UK for the United Kingdom and TW is for Taiwan.

Figure 3.2 illustrates that the returns of the three indices (i.e. equities, bonds and listed real estate) of the four countries (i.e. U.S., UK, Taiwan and South Africa) tend to move together-may be in tandem during the selected period. Musick et al (2018) stated that there is a very close trade relationship between the U.S., UK and Germany. Moreover, since the Brexit started (officially in January 2020). The UK has been forced to consolidate its trading opportunities beyond the European continent, and among countries that the UK consolidated trading relationships is America. Taiwan and South Africa are the allies of the U.S. in the far Asia and Africa, respectively. In the last few years, the U.S. has strengthened cooperation with those two emerging market countries. Therefore, that co-movements of the three indices of those four countries are unsurprising at all. The question is, does the pattern of co-movements of the indices influence investing patterns and/or behaviours.

Table 3. 1: PCA Results

Principal Component Analysis												
Parameter	PC(1)	PC(2)	PC(3)	PC(4)	PC(5)	PC(6)	PC(7)	PC(8)	PC(9)	PC(10)	PC(11)	PC(12)
Variance	7.1	2.3	0.83	0.77	0.34	0.24	0.16	0.12	0.07	0.03	0.03	0.01
Proportion	0.59	0.19	0.07	0.06	0.03	0.02	0.01	0.01	0.01	0	0	0
Cum. Proportion	59%	78%	85%	92%	95%	97%	98%	99%	99%	100%	100%	100%
Loadings	PC(1)	PC(2)	PC(3)	PC(4)	PC(5)	PC(6)	PC(7)	PC(8)	PC(9)	PC(10)	PC(11)	PC(12)
Equity-USA	0.366	0.044	0.027	0.208	0.011	0.076	-0.06	-0.004	-0.135	-0.12	0.361	0.805
Bond-USA	-0.295	0.199	-0.259	0.487	0.157	0.237	0.302	0.218	0.234	-0.228	0.454	-0.194
Real Estate-USA	0.321	0.26	0.053	-0.041	-0.238	-0.305	0.05	0.713	-0.215	-0.295	-0.07	-0.16
Equity-UK	0.159	0.502	-0.385	0.211	0.203	-0.404	0.294	-0.301	-0.146	0.239	-0.26	0.043
Bond-UK	-0.332	0.025	0.051	0.448	-0.179	0.319	-0.067	0.29	-0.176	0.233	-0.559	0.257
Real Estate-UK	0.066	0.538	0.448	-0.245	-0.163	0.484	0.351	-0.186	-0.139	0.028	0.043	-0.068
Equity-SA	0.317	0.277	0.098	0.156	0.252	0.178	-0.415	-0.09	0.513	-0.349	-0.353	-0.061
Bond-SA	0.293	-0.263	0.038	-0.121	0.712	0.264	0.291	0.312	-0.115	0.2	-0.125	-0.034
Real Estate-SA	-0.26	0.397	-0.048	-0.367	0.149	-0.081	-0.273	0.35	0.334	0.466	0.185	0.223
Equity-TW	0.344	0.047	0.076	0.361	-0.062	0.115	-0.427	-0.026	-0.227	0.486	0.307	-0.401
Bond-TW	-0.238	0.015	0.737	0.295	0.295	-0.466	0.049	-0.029	0.007	-0.003	0.069	0.019
Real Estate-TW	0.328	-0.208	0.12	0.147	-0.368	-0.084	0.415	0.071	0.608	0.347	-0.047	0.039

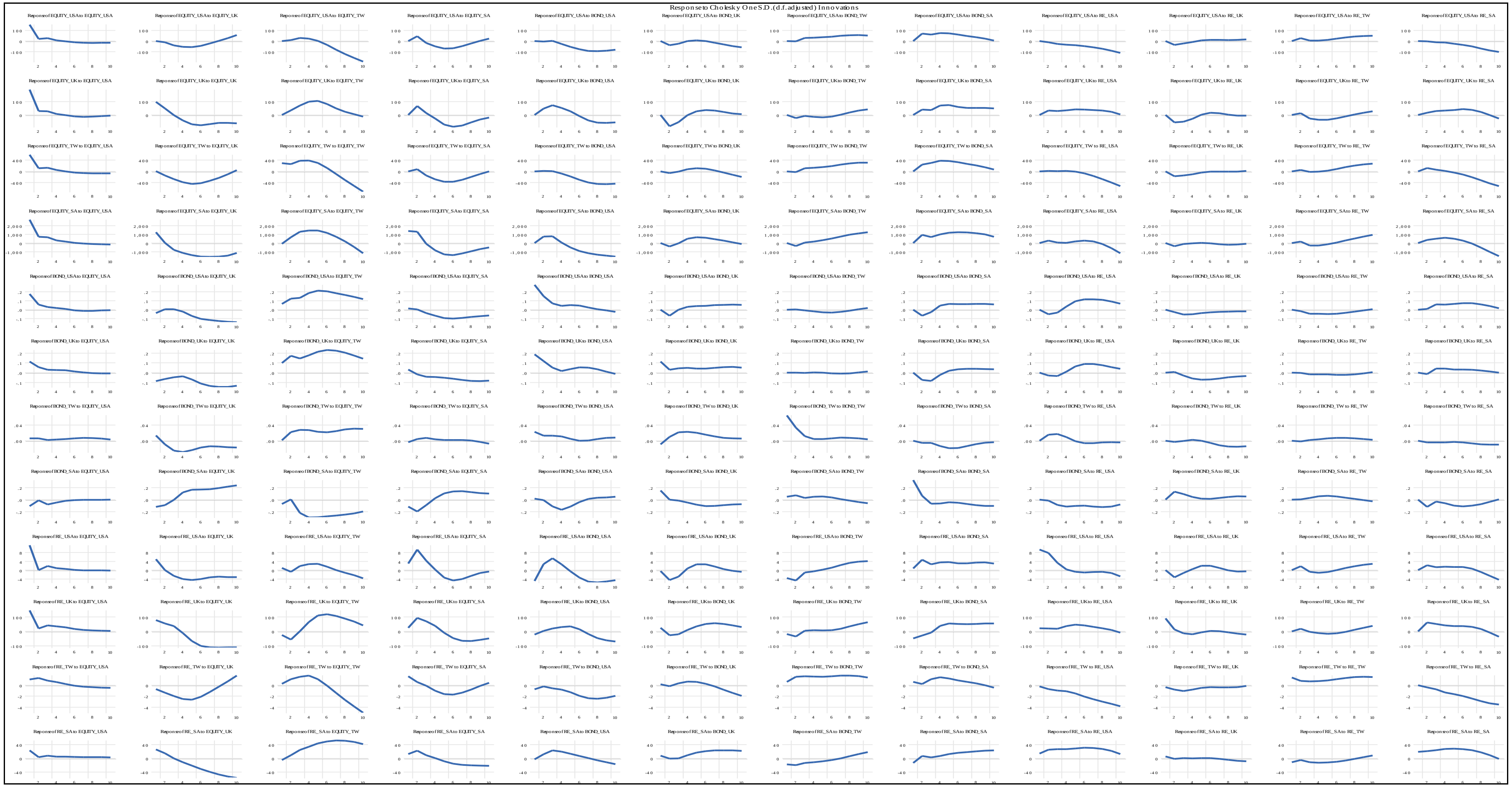
The variance, proportion of the variance and cumulative proportion is given in table 3.1. The number of factors retained was based off the Kaiser (1960) criterion which states that factors with a variance value that exceeds unity will be retained. Principal component parameters one to three have latent roots greater than one at 6.60, 2.71 and 1.06; respectively. The retained components are able to elucidate 86.4% (for the U.S. REITs) of the cumulative variance. The first principal component is able to explain 55% of the total sample variance. The second principal component is able to explain 77.6% of the total variation of the sample. The loading is a coefficient that indicates the relationship between the original variables and retained principal components, the higher the coefficient loading the stronger the relationship between the original variable and the retained principal component (Kola and Odongo, 2017). Following Liow et al, (2006), and Kola and Odongo (2017), loading coefficients that have an absolute value greater than 0.5 for each of the retained principal component. Principal component two (U.S. government bonds) has the highest positive correlation (0.496) with the UK REIT market. Principal component three (U.S. REIT market) is negatively correlation (-0.527) with the Taiwan REIT market.

Panel B of table 3.1 shows the second round of analysis of the retained factors, principal components one, two, three and four. Principal components one and two are greater than unity at 2.52 and 1.16. The retained components are able to elucidate 91.9% (for the U.S. government bonds) of the cumulative variance. The first principal component is able to explain 62.9% (U.S. equity markets) of the total sample variance. The loading coefficients show that principal component one (U.S. equity market) has the highest positive correlation (0.591) with the U.S. REIT market. Principal component two (U.S. government bonds) has the highest positive correlation (0.718) with the UK equity market. Lastly, panel C in table 3.1 shows the last round of analysis of the retained factors, principal components one and two. Principal component one is greater than unity at a value of 1.65. The retained component is able to elucidate 82.4% (for the U.S. equity market) of the cumulative variance. The first principal component is able to explain 62.9% (U.S. equity market) of the total sample variance.

The U.S. equity market, government bonds and REIT market have shown to be the dominant principal components. This is due to the dominance of the U.S. economy over global markets, the U.S. has the most substantial fund market with its mutual fund assets amounting to U.S.$ 11.6 trillion as of 2011 (Fang et al, 2017). Furthermore, the U.S. mutual fund is over 70 years old and holds 4770 equity funds thus the trading activities of U.S. fund managers greatly influence stock price as compared to trading activities of other investors or fund managers (Fang et al, 2017). The growth of U.S. REIT market can be attributed to the fact that the same country is the first country to introduce REIT legislation. Thus, the market is the largest (by market capitalization), most mature and established REIT market in the world (Kola and Odongo, 2017 and Stevenson, 2013) and U.S. government bonds are known to be great storer of value (He at al, 2016).

3.4.4 Robustness Test

Figure 3. 3: Cholesky Decomposition



Note: the Cholesky decomposition is read in conjunction with the VAR(1,1) results in table 3.1.

Table 3. 2: VAR(1,1)

Parameter	equity_USA	equity_UK	equity_TW	equity_SA	bond_USA	bond_UK	bond_TW	bond_SA	RE_USA	RE_UK	RE_TW	RE_SA
eqity_USA (-1)	-0.3676 (-0.5518)	-1.2169 (-1.3141)	-1.6339 (-0.5828)	-1.4436 (-1.0231)	-0.0010 (-0.7137)	-0.0009 (-0.7802)	1.03e-05 (0.0506)	9.13e-05 (0.0506)	-0.437 (-0.6024)	-0.2225 (-0.0261)	0.0119 (0.9932)	-0.3554 (-1.5891)
equity_UK (-1)	-0.2282 (-0.8442)	-0.0514 (-0.1368)	-1.0204 (-0.8968)	-9.9388 (-1.7354)	4.56e-05 (0.0770)	9.58e-05 (0.1952)	-0.0005 (-0.6275)	-0.0005 (-0.6275)	-0.0725 (-2.4612)***	-0.2990 (-0.8542)	-0.0029 (-0.6028)	-0.1537 (-1.6937)
equity_TW (-1)	0.1137 (0.9924)	0.1596 (1.0031)	1.1101 (2.3011)***	3.5249 (1.4517)	0.0003 (1.3639)	0.0003 (1.6596)	1.20e-05 (0.2298)	0.0002 (0.6506)	-0.0021 (-0.1677)	-0.0958 (-0.6452)	0.0018 (0.8871)	0.0034 (1.4119)
equity_SA (-1)	0.0346 (1.6062)	0.0359 (1.2011)	0.0059 (0.0651)	0.7877 (1.7281)	9.53e-06 (0.2022)	-2.71e-05 (-0.6939)	4.96e-07 (0.0505)	-3.86e-05 (-0.6631)	0.0032 (1.3497)	0.0032 (0.1132)	8.34e-05 (0.2161)	0.0034 (0.4743)
bond_USA (-1)	0.0367 (1.5453)	0.0769 (2.3249)***	0.1132 (1.1314)	0.8998 (1.7858)	0.5949 (1.1408)	-0.0112 (-0.0259)	-0.115 6(-1.0642)	0.0479 (0.0745)	0.0067 (2.5776)***	0.0475 (1.5415)	0.-0004 (-1.0207)	0.0176 (2.2057)***
bond_UK (-1)	-5.0338 (-2.7236)***	-7.5266 (-2.9291)	-0.1462 (-1.8800)	-0.7846 (-2.0042)***	-0.2691 (-0.6645)	0.593 2(1.7677)	0.2047 (2.4256)***	-0.1769 (-0.3534)	-0.0054 (-2.6842)***	-0.525 (-2.1952)***	0.0003 (1.1434)	-0.0134 (-2.1627)
bond_TW (-1)	-4.4950 (-1.4323)	-2.6585 (-0.6093)	-0.0601 (-0.4556)	-0.4926 (-0.7409)	-0.0214 (-0.0311)	-0.0329 (-0.0578)	0.5980 (2.4256)***	0.2910 (0.3424)	-0.0035 (-1.0247)	-0.0111 (-0.2719)	0.0012 (2.2668)***	-0.0039 (-0.3722)
bond_SA (-1)	0.0123 (1.4127)	0.0003 (0.2501)	0.0527 (1.4454)	0.2492 (1.3564)	-0.2242 (-1.1793)	-0.2219 (-1.4092)	-0.0286 (-0.7226)	0.2750 (1.1705)	0.0007 (0.8264)	-0.0016 (-0.1438)	-0.0001 (-1.1879)	0.0045 (1.5459)
RE_USA (-1)	0.2238 (0.0658)	3.9878 (0.8429)	-1.3638 (-0.0952)	1.7439 (0.2419)	-0.0055 (-0.7403)	-0.0024 (-0.3942)	0.0019 (1.2778)	0.0029 (0.3154)	0.8046 (2.1704)***	-1.9018 (-0.4316)	-0.0233 (-0.3813)	1.3158 (1.1517)
RE_UK (-1)	-0.3497 (-1.9181)	-0.6229 (-2.4577)***	-2.0284 (-2.6435)***	-4.2764 (-1.1073)	-0.0004 (-0.9654)	0.0001 (0.3398)	-2.76e-05 (-0.3319)	0.0017 (3.4993)***	-0.0363 (-1.8253)	0.0772 (0.3269)	-0.0062 (-1.9002)	-0.0665 (-1.0867)
RE_TW (-1)	0.1845 (1.6580)	0.1666 (1.0764)	0.8440 (1.8017)	2.5771 (1.0930)	-0.0093 (-0.3805)	-0.0064 (-0.3176)	-0.0031 (-0.6079)	-0.0470 (-1.5601)	2.1947 (1.8101)	0.0037 (2.6288)***	0.4120 (2.0645)***	5.2643 (1.4088)
RE_SA (-1)	-0.1115 (-0.1005)	0.8858 (0.5740)	6.0439 (1.2937)	1.8184 (0.7734)	0.0004 (0.1742)	-0.0007 (-0.3409)	-0.0002 (-0.4506)	-0.0063 (-2.0973)***	0.1135 (0.9387)	3.1511 (2.1923)***	-0.0203 (-1.0181)	5.2644 (1.4088)
F-Statistic	35.7559	3.7393	18.9681	4.8360	7.7327	23.8450	24.2694	9.1390	5.6068	3.7638	48.1651	15.6171
Akaike AIC	13.2106	13.8697	16.0850	19.3171	0.9640	0.5881	-2.1731	1.3881	8.7766	13.7275	5.1682	11.0278
Schwarz SC	13.8060	14.4651	16.6804	19.9125	1.5595	1.1834	1.5776	1.9835	9.3721	14.3229	5.7636	11.6232

Note: in each cell, the first number is the coefficient and the number in brackets is the t-test. In order for the t-statistic to be statistically significant for VAR values, the t-statistic should be at least 2 irrespective of being negative or positive, and *** illustrates that the t-statistic is at least 2. The VAR results should read in conjunction with Cholesky decomposition as illustrated in figure 3.2.

As illustrated in Kola (2021), the results of the VAR model should be read in conjunction with the Cholesky decomposition in order to get clearer interpretation of the results. Before running the VAR model, one needs to ascertain what number of lags are appropriate to demonstrate spillovers of variables and extension herding behaviour during investing stages of investments. Firstly, one ran difference-of-difference on all indices and results confirm that some indices shocks are explained by other indices-one lag might be appropriate. Thereafter, one ran a residuals autocorrelation test to confirm whether residuals are correlated or not-supports one lag. Finally, one ran the lag structure test to find out the lag length criteria based on one lag. The results show that Akaike AIC, Schwartz SC and Hannan-Quinn are statistically significant-supporting one lag.

Before presenting the results, one should note that the order of variables is important. For this study, one minimised the influences on the results, both in terms of size and liquidity. Therefore, for every index, one started with the U.S., followed by the UK, then Taiwan and finally, South Africa. The latter pattern is based on the descending order of the gross domestic products of countries. By extension, GDPs have positive influence of capital markets of countries. In terms of liquidity, the most liquid index is equities, then bonds and finally, the listed real estate. Kola (2021) opined that the order of variables matters when running the VAR model. Now, on the actual interpretation of the VAR results, one should interpret as follows. The responding changes in the first variable are due to changes of the lagged-shocks in the second variable. Put it precisely, it is always the row variable versus the column variable. The effects of the constant of the VAR model are unexplained by individual independent variable(s). Hence, the results of the constants are not interpreted in the study. Finally, in explaining the VAR results, one uses the t-statistic in brackets in table 3.2 and the t-statistic should be at least 2 irrespective of the sign before the number. Broadly, for most indices, the shocks from the first lags do not explain changes in the row variable. Despite that, there are interesting revelations. First, the UK equity index changes due to the lagged shocks from bond indices in the U.S. and the UK, respectively. For the latter variable, it would imply that the UK bond market is influential in market movements. It can be inferred from Papadamou et al (2019) that the UK bond market has a causal effect. On the UK equity versus the U.S. bond, that might be due to the close trading relationships between the two countries. Similarly, the South African equity index change to shocks from the UK bond index. On the other hand, the relationship between the UK and South Africa is historical deep for years. Secondly, the U.S. real estate index reacts to shocks emanating from the U.S. bond index. The same can be said about the U.S. real estate reacting positively to the U.S. bond index. The negative relationship in the former statement might be due to the fact that real estate has diversification benefits.

Other positive changes due to one-lagged shocks are due in Taiwanese bond to the UK bond, Taiwanese bond to its bond, Taiwanese real estate to Taiwanese bond, the U.S. real estate to its real estate, South African bond to the UK bond index, the UK real estate to Taiwanese real estate, Taiwanese real estate to its real estate and the UK real estate to South African real estate index. One thing known is that the countries have close relationships. For example, South Africa and the UK have similar structure and legislation in regulating capital markets. Gleason et al (2004) state that there is no symmetry of either upwards or downwards when investing in exchange traded funds (P681). Exchange traded funds are equity products. Therefore, based on the analogy from Gleason et al (2004), one can infer those negative reactions illustrated in other indices (the U.S. real estate to the UK real estate, the U.S. real estate to the UK bond, the UK real estate to the UK bond and South African bond to South African real estate index) exemplify potential herding behaviour of investing.

Lastly, on the robustness tests (i.e. F-statistic, Schwarz and Akaike) that support the VAR model, Kola (2021) assumed that one has the following inequality: (2,12)=22.59,p<0.05) and then, the critical value would be 1.22. Thus, every value of the F-statistic should be at least 1.22 irrespective of being positive or negative in order to be statically significant. The F-statistic measures the goodness of fit of a model and/or parameter. For the other latter two tests (i.e. Schwarz and Akaike), the critical range is 1.6 to 2.7-outside that range, it implies that the data is not normally distributed. Therefore. Most indices are not normally distributed and that might do with data points-33 points. Based on the argument of Kola (2021), it implies that most indices do not fit the model. Prior studies such as Messner and Pinson (2019) illustrate that for normal distributed VAR values one needs at 500 data points; however, the shorter data points still reveal salient findings of this study.

3.5 Conclusion

Firstly, existing relationships between countries influence herding in investing, particularly when those countries share similar statuses, such as being developed or not. Secondly, there is a correlation between listed real estate indices of the U.S. and Taiwan, with Taiwan being a solid partner of the U.S. in East Asia. Thirdly, herding can occur within and/or across similar and/or different indices. Fourthly, during the herding process, indices react to initial shocks emanating from other indices. Finally, most herding occurs among bond indices—bonds are the oldest capital market instruments and are likely the most widely used by various investors.

It has been shown that U.S. investors herd during the release of macroeconomic information, and there are also herding spillover effects from the U.S. to the U.K. markets at the onset of financial crises (Galariotis, Rong, and Spyrou, 2015). Additionally, the investigation revealed that U.S. investors herd due to both fundamental and non-fundamental factors during financial crises, while U.K. investors herd primarily due to fundamentals (Galariotis, Rong, and Spyrou, 2015).

The implications of this study are as follows. Firstly, investors should be aware that existing relationships influence investment behavior. Secondly, the intra- and trans-Atlantic relationships have a profound influence on different indices in terms of investment patterns. Thirdly, investors and underwriters need to develop more advanced techniques for calculating appropriate risk amounts during herding periods. Fourthly, indices are viable investment instruments. Finally, investment strategies need to be continually improved over time.

4 Herding of Volatility Patterns

4.1 Introduction to Herding of Volatility Patterns

Zwane (2024) studied herding behaviour of the three indices-(i) equities, (ii) bonds and (iii) real estate, comparing emerging and developed markets, where developed markets are represented by the United States of America (U.S., hereafter) and the United Kingdom (from here, UK) and emerging markets are Taiwan and South Africa. Zwane (2024) uses two models-principal component analysis (PCA) and the vector autoregressive (VAR). According to Zwane (2024), the reason why she used those four selected countries is to ensure that the results have a global presentation.

Fundamentally, the results of Zwane (2024) illustrate that the U.S. equity index contributes the most to the variation as confirmed by the PCA model. According to Buncic and Gilser (2016), the U.S. has the biggest listed equities, bonds, and real estate markets in the world. Furthermore, according to the authors, volatility spillovers emanating from the U.S. tend to influence other financial markets around the globe. However, Zwane (2024), provided opposing findings; the USA bond market significantly influences the UK equity market and the South African real estate market, while the USA real estate market significantly influences the UK real estate market; however, the equity market in the USA does not show a significant influence on other markets.

Moreover, the results of Zwane (2024), based on the VAR(1,1) and Cholesky decomposition confirm that shocks are largely among similar countries than different countries, in terms of country type. Thus, the one-lagged shocks for the UK are due to the unexpected stock market reactions from America. Similarly, the one-lagged shocks for South Africa are due to the unexpected reactions from the UK and Taiwan. This is because the UK is the largest European trading partner for South Africa, at least before the Brexit. Interestingly, the one-lagged shocks emanating in Taiwan for the three indices are due to the unexpected reactions from America. According to Caggiano and Castelnuovo (2020), the latter patterns are common during booms and busts, in particular when spillovers are uncertain.

Despite of the elegance of herding behaviour illustrations in Zwane (2024), the article, falls short when presenting to volatility patterns and spillovers during herding investing. Kola (2021) demonstrated that during transatlantic stock movements; volatility, especially volatility spillovers have major impact on investment decisions. Furthermore, volatility is the most widely used risk measure in finance and related subject areas (See; Merkle 2018). Then, the current study provides explanation for the patterns.

Thus, during herding behaviour, are volatility spillovers in this study different from volatility spillovers that are induced by transatlantic formations such as the U.S., the UK, Taiwan and South Africa countries? Furthermore, are there any unique issues emanating during volatility spillovers during herding investing? This study responds to these questions raised in this paragraph. Fundamentally, the results illustrate the following. First, during herding, the GARCH(1,1) results reveal that the reactions and persistence of volatilities are statistically significant. In addition, risks as presented by volatilities, converge to a point of the entire time series. Second, the lags, all from the one-lag to the fourth-lag, are statistically significant; both for out-of and in-sample time series. That consistency of the two-time series is rare indeed. Finally, the regimes across all countries irrespective of the products are interrelated with one another.

The balance of the article is structured as follows. Section 4.2 reviews prior literature. Section 4.3 is on modelling, in particular it outlines methods used in this study. Section 4.4 is on data. Section 4.5 focuses on the empirical analysis, while the last section concludes the study.

4.2 Literature Review

The literature reviews earlier studies that explored volatility patterns during herding behaviour in equities, bonds and real estate markets, including extrapolating methods that are appropriate for the analysis for this theme.

4.2.1 Equities

With the multiple crises witnessed in the financial markets over the last few decades brings to the foreground the intense influence investors psychology and behaviour alter market efficiency (Economou et al, 2018). Herding behaviour in financial markets is when a group of investors transact or buy and sell in the same direction over a period of time, these investors move in and out of markets as a group (Jirasakuldech and Emekte, 2021). Herding behaviour by financial players is deemed to be the largest cause of financial distresses in markets around the globe (Jirasakuldech and Emekte, 2021). Herding is characterized by excessive, rational, and irrational inclination of investors to disregard fundamental market information and trade in the same direction, which can destabilize the market and create; inefficiencies, excess volatility, give rise to the fragility of the financial system and create systemic risk (Jirasakuldech and Emekte, 2021). It is crucial to identify and assess herding and the associated feedback trading behaviours of investors when investigating and understanding the time series dynamics of asset prices due to their latent ability to initiate as; excess volatility, momentum and reversals in financial markets King and Koutmos (2021).

Herding behaviour is considered the agent that gives rise to events such as the global financial crisis, stock price instabilities and bubbles if it is driven by non-information-based reasons (Kizys et al, 2021). Herding may also cause a rise in the degree of co-movement between financial asset returns which then lowers the inherent advantages of portfolio diversification (Kizys et al, 2021). Christie and Huang (1995) are the pioneers in investigating the conjecture that U.S. investors tend to cluster around the market during the period of market stress.

Volatility in capital markets is a key research area in in finance; it informs pricing models, risk management strategies and investment decisions and the measurement thereof (Blasco et al, 2012). Volatility results as a consequence of the constant adjustment of stock prices to new information, however, volatility may also be caused by market conditions and herd behaviour (Blasco et al, 2012). Friedman (1953) initially found that irrational investment decisions by investors destabilized prices through buying at high prices and selling at low prices and rational investors drive prices to their fundamentals through buying low and selling high. Thus, volatility is driven by uninformed or liquidity trading, given that price adjustments arising from uninformed trading tend to revert (Blasco et al, 2012). Information asymmetry may drive volatility and that uninformed investors largely tend to follow the market trend, buying when prices rise and selling when they fall; a behaviour that we might consider tantamount to herding (Blasco et al, 2012).

Literature has shown how herding threatens financial stability of markets around the world by worsening the volatility in returns (Duygun et al., 2021). It is for this reason that Duygun et al. (2021) investigated herding during periods of volatility on the two sides of the Atlantic. The study by Duygun et al. (2021) presented verification that herding behaviour is more prominent during periods of high volatility as well as illiquidity and credit deterioration.

The study made use of quantile regression analysis to detect if herding is sensitive to the varying quantiles of the returns' dispersion in the equity markets of the U.S. and the Eurozone, this method considers the tails of the distribution which would normally be lost with the linear regression model (Duygun et al, 2021). Herding behaviour was detected using the cross-sectional dispersion of stock returns using the Cross-Sectional Absolute Deviation model developed by Chang et al. (2000) during the global financial crisis and the Eurozone crisis. Daily equity prices were collected from the S&P500 and S&P Europe 350, with a sample period that runs from 3 January 2005 to 29 December 2017.

Duygun et al. (2021) observed herding during the global financial crisis in the U.S. and Eurozone in the equity markets, and there was no significant herding during the Eurozone crisis in both the U.S. and the Eurozone equity markets. However, herding during the Eurozone crisis was found in other financial sectors in the U.S. and the Eurozone. It has also been observed that herding is more probable in the U.S. in the time of extreme market distress with higher volatility (Duygun et al, 2021). During the global financial crisis, the herding observed was more spurious than intentional, whereas herding during the Eurozone crisis the herding was based on non-fundamental information also known as intentional herding (Duygun et al, 2021). The investigation has shown that herding during high volatility periods of the economy prevails more in the extreme parts of the Cross-Sectional Absolute Deviation distributions due to the fact that smaller capped stocks are more susceptible to intensive manipulations attracting herding related to these assets (Duygun et al, 2021).

An investigation of herding behaviour under different stressful and volatile periods of the Thai equity market by Jirasakuldech and Emekte (2021) revealed that investors herd in the down (bearish) market and very few investors herd in the up (bullish) market, confirming the asymmetric nature of herd behaviour. Furthermore, during periods of high market turbulence and uncertainty herding by investors was detected. The study reviewed herding under natural, financial, and political crises from the Asian crisis in 1997, Russian Ruble crisis in 1998, NASDAQ bubble crisis in 2000, the 2001 Terrorist attack, 2004 Tsunami, the political coup of 2006 and lastly, the 2008 mortgage subprime crises (Jirasakuldech and Emekte, 2021).

Herding was detected in the Asian, Russian Ruble and 2000 Technology crises, on the other hand the terrorist attacks on the 11th of September 2001, the tsunami of 2004 and the Thai political coup of 2006 as well as the subprime mortgage crisis did not trigger any herding by investors (Jirasakuldech and Emekte, 2021). The findings of herding behaviours during the Asian crisis from 1994 to 1997 are verified by the structural break point analysis. A rolling regression was performed which confirmed that herding behaviour occurred intensely in Asian in 1997 for all sectors, but not in other crisis periods (Jirasakuldech and Emekte, 2021).

Jirasakuldech and Emekte (2021) measured herding in the Thai equity market by investors using the dispersion of equity returns, a tool commonly used in this topic-CSAD. The analysis included a review of how investors behave during; bullish and bearish markets, high and low trading transaction volumes, around the crisis dates, market structural changes, business cycles and employed a structural break point test for robustness (Jirasakuldech and Emekte, 2021). The data collected from the Thai stock market ran from January 1988 to July 2015, consisted of daily price indices and trading volumes of about 660 companies.

The global covid-19 pandemic sent shock waves and strained health care system around the world and has triggered government responses to assist and alleviate the health, societal, and financial stress brought on by the covid-19 pandemic (Kizys et al, 2021). The corona virus pandemic was set to bring about a global recession and financial crisis which led to market uncertainty, panic sales and in certain instances herding by investors. Kizys et al, (2021) detected investor herding in global stock markets during the coronavirus pandemic, whether the government response eased herding amongst investors and lastly, whether short-selling restrictions in the European Union were useful in curbing herding. It is hypothesized that the shock of the global covid-19 pandemic may cause volatility and instability in the global economy which may or may not trigger herding in global stock markets.

Seventy-two international stock market indices from emerging and developed countries were collected from the Thomson Reuters database from January 2020 to 31 March 2020. The investigation was conducted with the use of the CSAD and CSSD tools as herding measures, the government response was detected using the Oxford Covid-19 government Response Tracker through a Stringency Index (Kizys et al, 2021). A panel data regression was used to determine the effects of the government intervention and the restricted short-selling, the panel data regression results were verified using a quantile regression which was also used to consider the conditional distribution of the herd behaviour (Kizys et al, 2021). A robustness test was conducted using principal component analysis (PCA) to verify the main findings and verify the reliability of the Oxford Stringent Index.

The study found evidence of herding during the first quarter of 2020 in the midst of the covid-19 pandemic (Kizys et al, 2021). A decrease in the CSSD/ CSAD indicators confirms that stringent government response to the crisis mitigates herding by investors by reducing uncertainty regarding the crisis (Kizys et al, 2021). Lastly, the study observed lower levels of herding by investors where short-selling restrictions were imposed (Kizys et al, 2021).

King and Koutmos (2021) investigate how herding behaviour and feedback trading drive price movements in nine cryptocurrencies, namely: bitcoin, electro-optical system, stellar, ethereum, ripple, bitcoin cash, litecoin, IOTA and cardano. Cryptocurrencies are known to encounter significant bouts of price volatility, it is thus important to ascertain if herding behaviour exists in this market, as well as the direction of the herding behaviour in response to lagged returns (King and Koutmos, 2021).

Nine cryptocurrencies were sampled for this investigation, the sample period ran from the varying introduction of the respective cryptocurrency to the 8th of June 2020 and consists of the daily closing prices of the cryptocurrencies. The study made use of regression models, VAR and EGARCH, to detect herding behaviour and determine if lagged negative returns are amplified during herding (King and Koutmos, 2021). The regression models are advantageous due to their ability trace and detect herding (King and Koutmos, 2021). The results of the study by King and Koutmos (2021) indicate that a few of the cryptocurrency (bitcoin, ethereum, ripple, cardano) exhibit trend chasing/herding (i.e., positive feedback trading), while the other cryptocurrencies (EOS and stellar) exhibit herding in the opposite direction-contrarian trading (i.e. negative feedback trading).

Majority of the literature on herding focuses on developed markets or a group of more eminent emerging markets, emerging market investors are considered to be speculators, and their trading causes the significant market volatility (Jirasakuldech and Emekte, 2021). Herding behaviour is known to be the cause if the recent crises in these last few decades, from the global financial crisis to price bubbles which have led to widespread instability and volatility across financial markets. The unfortunate ramifications that stem from herding behaviour show the importance of investigating the relationship between herding behaviour and the associated volatility and instability.

4.2.2 Bonds

Gupta et al. (2019) carried out an empirical study to prove the theoretical that rare disaster risks have an impact on the market returns and volatility of government bonds. The investigation was prompted by earlier works of theoretical models and claims that rare disaster risks affect movements of asset prices (Gupta et al, 2019). And the increasing likelihood of a disaster generates a fall in investment and leads to the risk of recession. These earlier works were plagued with the problem of having small sample sizes due to the fact that individual countries rarely experience major disasters (Gupta et al, 2019). This was circumvented in studies by Berkman et al. (2011; 2017) who focused on a much bigger sample of probable disasters that are more likely to lead to changes in perceived rare disaster probabilities.

The study by Gupta et al. (2019) used a detailed databank of all worldwide political crises, named the international crisis behaviour project databank to determine the prognostic power of rare disaster risks for the volatility and return of 10-year government bonds of the U.S., the UK and South Africa. Monthly U.S. data from January 1918 to December 2013, UK data from January 1933 to December 2013 and South African data from January 1918 to December 2013 was collected to conduct the investigation. The study modelled volatility with the use of GARCH-GARCH (1,1) model and conducted another causal test using the causality-in-quantiles test. The predictive analysis was based on the *k*-th order nonparametric causality-in-quantiles test developed by Balcilar et al. (2017).

The results of this causality-in-quantiles test revealed that rare disaster risks do not affect returns but volatility of the 10-year government bonds of the U.S., the UK and South Africa (Gupta et al, 2019). It is worth noting that government volatility is able to predict equity premiums which speaks to the interconnectedness of these asset classes (Gupta et al, 2019).

Predictability was detected from the rare disaster risks on bond market volatility in the U.S., however, there was no causality observed in the UK and South Africa (Gupta et al, 2019).

Pension funds play a significant role and impact on the financial market due to the fact that a substantial portion of pension funds are invested in government bonds, thus the behaviour of pension funds may shift securities away from their price equilibrium and bring about abnormal volatility (Koetsier and Bikker, 2021). The Dutch pension system is relatively developed, and pension funds in other countries move in the direction of the Dutch pension system on account of pension reform the aging population (Koetsier and Bikker, 2021).

Koetsier and Bikker (2021) explored how the behaviour of Dutch pension fundholders in the long-term sovereign bond market during times of crisis and peace, the data collected was of monthly pension fund holdings data broken down into sales and purchases, revaluations, exchange rate and other adjustments. The study will also investigate whether or not herding behaviour has a stabilizing or destabilizing effect on the market. The data of Dutch pension fundholders was collected from the De Nederlandsche Bank, it was a total of 67 of the largest Dutch pension funds from December 2008 to December 2014. The study used the well-known Lakonishok et al. (1992) model to measure herding. Herd behaviour contributes to stability in sovereign bond markets during periods of crisis. However, destabilizing behaviour takes place during periods of non-crisis or for safe-haven markets that are better well-resourced to manage the effects (Koetsier and Bikker, 2021).

Benlagha and Hemrit (2021) sought to find the determinants of the link between sovereign bond yields in the G7 countries with the use of the panel data model. The investigation centres around the impact economic policy uncertainty on the affinity patterns between the seven bond yields (Benlagha and Hemrit, 2021). Literature has shown how numerous financial crises lead to increased spillovers between global financial markets, and sovereign bonds are the most directly affected financial asset (Benlagha and Hemrit, 2021).

Investigations around bond yield spillovers and connectedness have led to feeble predictive laxity and robustness of empirical testing due to studies that focused on isolated and/or small sample of economies and studies that have focused on the impact of the benchmark term structure of interest rates on bond risk premia, spread the first moment and assume a non-informational interaction between sovereign bond volatilities (Benlagha and Hemrit, 2021). The study by Benlagha and Hemrit (2021) examined the dynamic spillovers and connectedness between sovereign bond markets of the U.S., France, the UK, Italy, Japan, Canada, and Germany from January 2015 to December 2019. Previous research ignored the impact of time horizons on the connectedness between assets (Benlagha and Hemrit, 2021). Bond maturity is a dominant variable that may have an impact on the dynamic patterns of connectedness between sovereign bonds (Benlagha and Hemrit, 2021). The authors considered the varying bond maturities that have been previously ignored as well as the factors that influence of the dynamic patterns of connectedness among bond yields.

The study evaluates the sensitivity of the connectedness, spillovers, the effect of macroeconomic factors as well as economic policy uncertainty on the dynamics of connectedness on the sovereign bond yields (Benlagha and Hemrit, 2021). The authors used a VAR based spillover index approach by Diebold and Yilmaz (2012) to effectively evaluate the amount of connectedness over various assets in a time series is to make use a VAR process and assess its forecast error variance decomposition (Benlagha and Hemrit, 2021).

The investigation revealed that the total volatility connectedness is significantly high across all G7 economies' two- and thirty-year sovereign bond yields; however, the total affinity increases with the time horizon of the sovereign bonds (Benlagha and Hemrit, 2021). Benlagha and Hemrit (2021) showed that the patterns of the dynamic association differ between the G7 countries and with the time horizon of the selected sovereign bonds. The differences are linked to a number of economic and political shocks namely, the 9/11 terror attacks of 2001 and the 2008 subprime mortgage crisis in the U.S., the 2016 Brexit referendum in the UK. Lastly the Greek bailout in Europe (Benlagha and Hemrit, 2021).

Upon the outbreak of the COVID-19 pandemic, governments across the globe implemented policies to mitigate the economic and non-economic effects of the pandemic, which also resulted in a number of studies investigating the impact of government policies on international stock markets (Zaremba et al, 2021). The increased uncertainty and the unstable business conditions brought about by the pandemic lead to volatility in the bond market (Zaremba et al, 2021). There are two school of thoughts with regards to how government interventions affect bond volatility. First, it is postulated that risks brought about by uncertainty and unstable business conditions can be mitigated by the intercession of government (Zaremba et al, 2021). The second school of thought hypothesizes that government intervention may cause further uncertainty regarding current and future interventions, which may be conducive to higher bond volatility (Zaremba et al, 2021). Volatility can increase as follows: 1) through fiscal stabilization policies which increase uncertainty regarding future tax pressure; 2) uncertainty around changes in future inflation overrides uncertainty around the economic effects brought on by governments response and 3) if the government's response includes public spending plans, which then causes positive bond term premia via a positive relation between marginal utility and inflation (Zaremba et al, 2021).

Zaremba et al. (2021) seek to explore the gap of government policies in response to the COVID-19 outbreak and which school of thought bond volatility. The study investigated 31 developed and emerging economies during the COVID-19 pandemic from the following regions: North America, Europe, Asia, Oceania, and Africa (Zaremba et al, 2021). The volatilities are quantified using the Datastream 10-Year Government Bond Total Returns indices, the sample period covered the pandemic period from January 2020 to September 2020 and the data was analysed using panel regressions. Volatility was measured based on methods used in Antonakakis and Kizys (2015) and Khalifa et al, (2011). The study postulates that COVID-19 government intervention stabilized sovereign bond markets and was instrumental in decreasing volatility (Zaremba et al, 2021).

Galariotis et al. (2016) observed on bonds, periods of volatility in the global bond market and postulated that market bond volatility may further drive herding behaviour. According to Cai et al. (2019), herd behaviour will result in market inefficiency and excess price volatility. When herding occurs it drives large, transitory pressure on bond prices which drives bond prices significantly away from their fundamental values and distorts values causing excessive price volatility in the bond market (Cai et al., 2019). It is for this reason that the study of the relationship between herding of bonds and volatility during, prior or after is essential in order to ascertain how to best hedge against it or diversify it, which is vital for investment decisions and risk management (Raddartz and Schmukler, 2021).

4.2.3 Real Estate

Cui et al. (2019) investigated investors herding in closed-end funds. A closed-end fund is a pool of similar assets put together for common investment goals for a specific period, usually for a longer duration. Other names used for closed-end funds are closed-end investment and closed-end mutual fund. Thus, the definition of closed-end funds encompasses REITs as well. The similarities between closed-end funds and REITs include (i) both having high similar risk (Myer and Webb, 1993) and (ii) have similar trading strategies (Wang et al, 1992). From synthetization of literature, Cui et al. (2019) found out that herding reduces information asymmetry. The theoretical background in structured as follows. First, herding, then closed-end funds and finally hypotheses. From the first pillar, the authors argue that herding behaviour is usually driven by equities and herding tends to be market-wide in terms of behaviour. The second stream, the theoretical background shows that closed-end funds similar traits to REITs-share prices trade below their net asset value per share (from here, NAV), closed-end funds invest in specific assets for their entire life, and some funds focused on a buying strategy and others doing the selling strategy (P196). On the hypotheses, they focused on whether there is herding behaviour in closed-end funds.

For methodology, Cui et al. (2019) used the CSAD model in four different ways-(i) absence of herding in markets, (ii) herding on up/down market day, (iii) herding in low and high volatility and (v) herding during low and high volumes. Another technique used by Cui et al. (2019) is the value-weighted discount index. The data is on the U.S. closed-end funds; daily prices, net asset values, market capitalizations and trade volumes from January the 2^{nd}, 1992 to December the 13^{th}, 2016. The descriptive statistics show that discounts and value-weighted discount index are negative skewed while CSAD approach, market returns, percentage of deviation and premiums are positively skewed. For CSAD model, results confirm that investors herd in closed-end funds. Using the VIX index as proxy for volatility, results reveal more herding in volatile markets. The latter finding on herding during volatile markets were confirmed earlier by Kallberg et al. (2002), and Zhou and Anderson (2013). The results show that herding is noise driven according to Cui et al. (2019). In the context of REITs, herding is most likely to be evident, specifically if one uses NAVs given that NAVs capture more information than share prices in listed real estate industry. The value-weighted discounted index confirmed that prices deviate during herding periods. The robustness tests applied by Cui et al. (2019) confirm that the earlier findings stay. Interestingly, on the robustness tests, the authors opine that the reason for herding is to hedge uncertainty by mimicking the trades of their peers.

Ngene et al. (2019) studied spatial time-varying heterogeneity of volatility shocks based on the metropolitan statistical area housing markets in America. The advance a view that volatility movements are important for scholarship because housing forms an important part of the national economy. And the worsening situation on the housing markets leads to declining property taxes and by extension, local government finances (Ngene et al, 2019). The central investigation in Ngene et al. (2019) is determining ‘behaviour of conditional volatility after major shocks captured in the news’ (P26-27). One of the reasons why the metropolitan statistical areas are included in the study is because the metropolitan statistical areas may evolve into superstar cities according to the authors. Therefore, the wealth changes coming from the metropolitan statistical areas, might have future impact on the wealth of the American nation. They retrieved data from Case-Shiller House Price Indices, covering 20 U.S. metropolitan statistical areas-Atlanta, Boston, Charlotte, Chicago, Cleveland, Dallas, Denver, Detroit, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa Bay and Washing DC.

For the 14 metropolitan statistical areas, their data is from 1987:01 to 2018:06, while for Atlanta, Dallas, Detroit, Minneapolis, Phoenix and Seattle, whose data series start on 1991:01, 2000:01, 1991:01, 1989:01, 1989:01 and 1990:01, respectively. For econometric analysis, Ngene et al. (2019) started with Hannan-Quinn criterion for choosing the lag because according to the authors Hannan-Quinn criterion works best when sample size is at least 60. For the actual econometric modelling of conditional volatilities, they used autoregressive conditional heteroscedasticity (ARCH) and GARCH. Because Ngene et al. (2019) did not want to impose artificial non-negative constraints in the model, they accounted for exponential movements in those models. Hence, they ended up with ARMA(2,2), TGARCH and EGARCH models. Kola (2021) showed that GARCH(1,1) can be strengthened to become an integrated model by capitalizing it-extending GARCH(1,1) such that it can account for capital structure of firms. Despite of the elegance of EGARCH and TGARCH, Ngene et al. (2019) opine that the two models fall short when capturing good and bad news of stock markets. Therefore, GARCH family models should be used in conjunction with models that account for different regimes such as Markov-regime switching model.

First virtual presentations illustrate that; Atlanta, Las Vegas, Minneapolis, San Francisco, Phoenix, Seattle and Tampa Bay had higher volatility than the rest of the metropolitan statistical areas. The ARCH results confirmed heteroscedasticity, which implies that time-varying effects should be accounted for by the authors. Furthermore, the authors opine that volatility clustering suggests that occasionally, variance is either smaller or larger than standard unconditional variance. Using the PP test, Ngene et al. (2019) confirmed that housing market returns are stationery in the 20 metropolitan statistical areas. Based on TGARCH results, seven (Atlanta, Chicago, Charlotte, Cleveland, Dallas, Denver and Miami) out nine cities, exhibit immaterial ARCH results are Southern and Midwestern cities. Broadly, bad news increased volatility movements. “The intensification of volatility after bad news may be stoked by the fearful trading behaviour of investors”, Ngene et al. (2019:37-38). Other main findings include leverage being consistent with volatility feedback effect and the increase in volatility feedback effects increase housing returns. Contrary, that leads to a higher discount rate, which leads to lower housing values.

Ngene et al. (2019) went further and gave potential reasons for their findings. Based on borrowed literature, they opine reasons for their findings include (i) rapid house construction, (ii) changes in demand and (iii) broad housing inventory. Among notable features between metros include supporting amenities, which leads to some trading at a premium, different housing regulations including restrictions on housing stock. Based on those arguments, it can be inferred that pricy houses are more volatile than cheap houses. Overall, the authors inferred that volatility movements symbolizes herding behaviour of house investments. Fundamentally, investors herd from negative volatility to positive volatility environment as the latter case offer more investment opportunities. The robustness test is based on rerunning TGARCH and EGARCH models using recession dummies. Broadly, the robustness tests confirmed earlier findings of Ngene et al. (2019). Interestingly, the superstar cities (New York, Boston, Los Angeles, San Francisco and Washington DC) exhibit upward slopping patterns while Southern and Midwestern cities exhibiting down slopping patterns. In the context of herding investing, investors would herd from Southern and Midwestern cities to superstar cities.

Bae et al. (2019) investigated herding phenomena when the phenomena is underpinned by stock market dynamism. The dynamism is from the combined effect of (i) 'non-coordinated collective interactions between agents and (ii) con-current reactions of agents to market signals' (P365). According to the authors, collective behaviours include (i) aggregation, (ii) fads, (iii) fashion, (iv) flocking and (v) herding. The point of interest for Bae et al. (2019) is that the particle-based flocking model that herding behaviour of agents. In building their herding model, they departed from the point of N agents and M assets. Their key assumption is that 'no new players or assets enter or exit the market' (P367). Then, they denoted agent and velocity models. Among key inclusion in the model is a dynamic market signal, function $w(x, t)$. Other inclusions of the model are the noise term, synonymous with the stochastic price model. Based on the literature synthetization, Bae et al. (2019) opined that herding occurs when there are two agents, and one agent imitates another agent even though the following agent has information which contradicts the following of another agent behaviour. The theory that underpins Bae et al. (2019) is swarm approach. Finally, the particle-based flocking model is customized to have symmetric argument. Thereafter, they constructed herding functionals, which led to formation of covariance functionals and weighted covariance functionals. Other supporting functions built by Bae et al. (2019) are (i) exponential herding and (ii) herding without decaying rate. Moreover, derivation of functions of the particle-based flocking model, see pages 373-386 of Bae et al. (2019).

The estimations are based on Gronwall type estimate and LaSalle type invariance property. The numerical simulations are based herding behaviours demonstration in the market. Test one is for numerical verifying whether there is an explicit herding rate, and herding rate can be replaced. Test two is for solution for 'herding in a multi-dimensional case' (P368 and test three is on determining herding positions and velocities of a histogram. Test one is 2 asset and 5 players. Test one confirms herding behaviour; moreover, there is convergence which is closer to 5 and that 5 corresponds with the slope of linear increase in a position. That would be similar to regime switch at an eventful date. According to the authors, the first agent has strong asymmetric information at that date. And when the position and velocity are considered in the presence of an influential market player, the outcome is different from the first case. First, irrespective of the position of the eventful date, ultimately, the herding behaviour follow a futuristic pattern. As velocities change, initially, there will be different spiky movements which ultimately level out at a future date.

When there are average market expectations, the resulting herding behaviour patterns are similar as the earlier cases/findings. When times evolve, given herding energies and pairwise distance, the patterns herd from a high base to a low base. Finally, as herding starts to enter decaying phases, then resulting patterns are of a polynomial function. Fundamentally, polynomial functions incorporated interlinked structures of parabolic and inverse parabolic shapes. Sebehela (2021) illustrated that parabolic functions create an environment to increase profit margins. Therefore, it is probable that in a herding environment, investors can make more margins than initially anticipated based largely on how herding margins are modelled. Then Bae et al. (2019) went further and did verification of earlier results and robustness check. According to the authors, the salient from results verification is that herding energy does not decrease monotonically. It can be inferred from Heidary et al. (2020) that energy dissipates with time. On the robustness test, Bae et al. (2019) illustrated that the herding behaviour stays irrespective of the choice of parameters. After test one, they moved to tests two and three, respectively. For test two there are 2 assets and 4 players, while for test three, there were 2 assets and 500 players. Fundamentally, the findings are similar to ones in test one.

4.3 Modelling

4.3.1 Preface

First, this study presents whether during the time series data, the selected markets were in bull and/or bear states. In order to illustrate this, the study uses the GARCH model. It can be inferred from Jawadi et al (2019) that the GARCH family models are elegant in illustrating bull and bear markets. From the GARCH family models, the model of interest is GARCH(1,1); first, it is a conditional volatility, which will illustrate any conditional behaviour in the indices. Second, The GARCH(1,1) model has the lambda (λ) parameter, which explains the effects of leverage. The leverage effect in the context of the GARCH model refers to the observation that stock returns tend to be more volatile when the market is down than when it is up (Jawadi et al., 2019). This is because a decrease in asset prices can lead to an increase in the leverage ratio (debt-to-equity ratio) of a company, which in turn can increase the perceived risk and volatility of the stock (Jawadi et al., 2019). The leverage effect is a nonlinear effect that can be captured in the GARCH framework by incorporating leverage terms in the model specification (Jawadi et al., 2019). Brooks (2008,pp380) defines the leverage effect as “ the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude”. In the context of the REIT industry, the elegance of GARCH is illustrated in Kola (2021). The formula for the GARCH(1,1) model is as follows.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4.1a}$$

where $\omega > 0$, α, β and $\lambda \geq 0$. And ω is a constant variance coefficient, α captures reaction of the volatility to market events, β determines the persistence in volatility and $\alpha + \beta$ determines the rate of convergence of the conditional volatility to the long-term average level. Further, $\alpha + \beta = 1$ otherwise the model "explodes" and σ_{t-1}^2 is the spot variance. Given that debt is inherent in the indices, especially in the real estate industry, which is the major component of funding, then account for debt/leverage in the GARCH(1,1) model is appropriate. According to Kola (2021), when GARCH(1,1) incorporates a leverage effect, usually called lambda (λ), eq. (4.1a) expands into;

$$\sigma_t^2 = \omega + \alpha(\varepsilon_{t-1} - \lambda)^2 + \beta\sigma_{t-1}^2 \tag{4.1b}$$

where λ captures the leverage effect and $\lambda \geq 0$. Eq. (4.1b) is the one used to calculate the GARCH(1,1) parameters.

4.3.2 Main Modelling

For the actual testing of herding behaviour, this study proposes using VAR model. Kola (2021) have used the VAR model in a similar setting before. The formula for VAR is;

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \mathrm{e}_t \tag{4.2}$$

where the l-periods back observation y_{t-1} is called the l-th lag of l-th lag of y, c is a $k * 1$ vector of constants (intercepts), A_j is the time-invariant $k * k$ matrix and e_t is a $k * 1$ vector of error terms satisfying $\mathrm{E}(\mathrm{e}_t) = 0$, every error term has mean zero. Just like any empirical work, it is important that the main findings, at least should be validated and/or supported by a robustness test in order to ascertain the key revelations.

4.3.3 Robustness Test

In order to have a deeper insight into the herding behaviour, this study proposes using a regime-switching model in order to capture different spillover regimes. The common model used for regime-switching variables is the Markov switching model (Fatnassi et al, 2014). A simple switching model for the variable z_t involves two AR specifications:

$$z_t = \begin{cases} \alpha_0 + \beta z_t + \varepsilon_t, s_t = 0, \\ \alpha_0 + \alpha_1 + \beta z_t + \varepsilon_t, s_t = 1, \end{cases} \tag{4.3}$$

where $|\beta| < 1$ and ε_t are i.i.d. random variables with mean zero and variance σ_ε^2. This is a statitionay AR(1) process with the mean $\frac{\alpha_0}{1-\beta}$ when $s_t = 0$, and it switches to another stationary

AR(1) process with mean $\frac{\alpha_{0+\alpha_1}}{1-\beta}$ when $s_t = 1$. If $\alpha_1 \neq 0$ then the model admits two dynamic structures at different levels, depending on the value of the state variable s_t. In this case, z_t are governed by two regimes with distinct means, and s_t determines the switching between two different regimes.

4.3.4 Conclusion of Modelling

Note that the choice of univariate [i.e., GARCH(1,1) and Markov-regime switching] and multivariate (i.e., VAR) models in detecting whether individual behaviour and/or effect is inherent in the individual index can be mirrored by the portfolio that includes that index among other indices. Thus, the question why in terms of mirrorage, there answer either yes or no, when one compares stand-alone behaviour index versus the same index in a portfolio of indices that includes the stand-alone index.

4.4 Data

Weekly data of three asset classes (equities, bonds and listed real estate) from two developed markets (the U.S. and the UK) and emerging markets (South Africa and Taiwan) were collected from the January 2013 to November 2021 from the Bloomberg terminal. The selected countries are major players in their respective geographies; moreover, the choice of countries makes it a global sample. The indices used for the analysis are as follows. For the U.S. – (i) S&P500 all share index, (ii) the U.S. 30yr government bond and (iii) the Bloomberg U.S. REIT index, and for the UK – (i) FTSE all share index, (ii) the UK 30yr government index and (iii) FTSE 350 REIT index; Taiwan – (i) Taiwan stock exchange weighted index, (ii) the 30yr government index and ((iii) S&P Taiwan REIT index and for South Africa – (i) FTSE/JSE Africa all share index, (iii) FTSE/JSE Africa South African listed property index and (iii) the South African 30yr government bond index.

The U.S. based equities index (S&P 500 index) is considered the best gauge of large-cap U.S. equities and is made up of eleven sectors and twenty-four industry groups. It constitutes five hundred large-cap companies that trade on the American Stock Exchanges. The index is made up of 80% of Americas equity market by capitalization. The FTSE all share index is made up of eleven sectors and represents approximately 98% to 99% of the UK equity market capitalization, originally named the FTSE Actuaries all share index. It is made up of around two thousand companies that trade on the London Stock Exchange. The Taiwan weighted index represents companies listed on the Taiwan Stock Exchange; it was first published in 1967. The

FTSE/JSE Africa all share index is the South African equity index and made up of eighteen sectors. Formerly known as the JSE actuaries index, the index constitutes 99 percent of the market capitalization of securities listed on the Johannesburg Stock Exchange. The study made use of the 30-year government bond for all four markets. The U.S. REITs is comprised of twelve real estate sectors and at least 95% of the U.S. REIT firms are specialised (See; Benefield et al, 2008). According to Benefield et al. (2008), the benefits (costs) of specialisation (diversification) out way the costs (benefits) of diversification (specialisation).

The UK REIT index is made up of fifty-nine companies with a total market cap of fifty-five billion at the end of June 2020. The UK REIT firms are focused on diversified REITs. The Taiwan REIT sector has five REIT companies listed on the Taiwan Stock Exchange which focus mainly on diversified REITs. Lastly, the South African listed real estate constituents of at least twenty of the largest shares listed on the Johannesburg Stock Exchange in real estate investment and services, and the real estate investment trust sectors

4.5 Empirical Application

4.5.1 GARCH(1,1) Results

4.5.1.1 Out-of-Sample

Figure 4. 1: Out-of-sample log returns

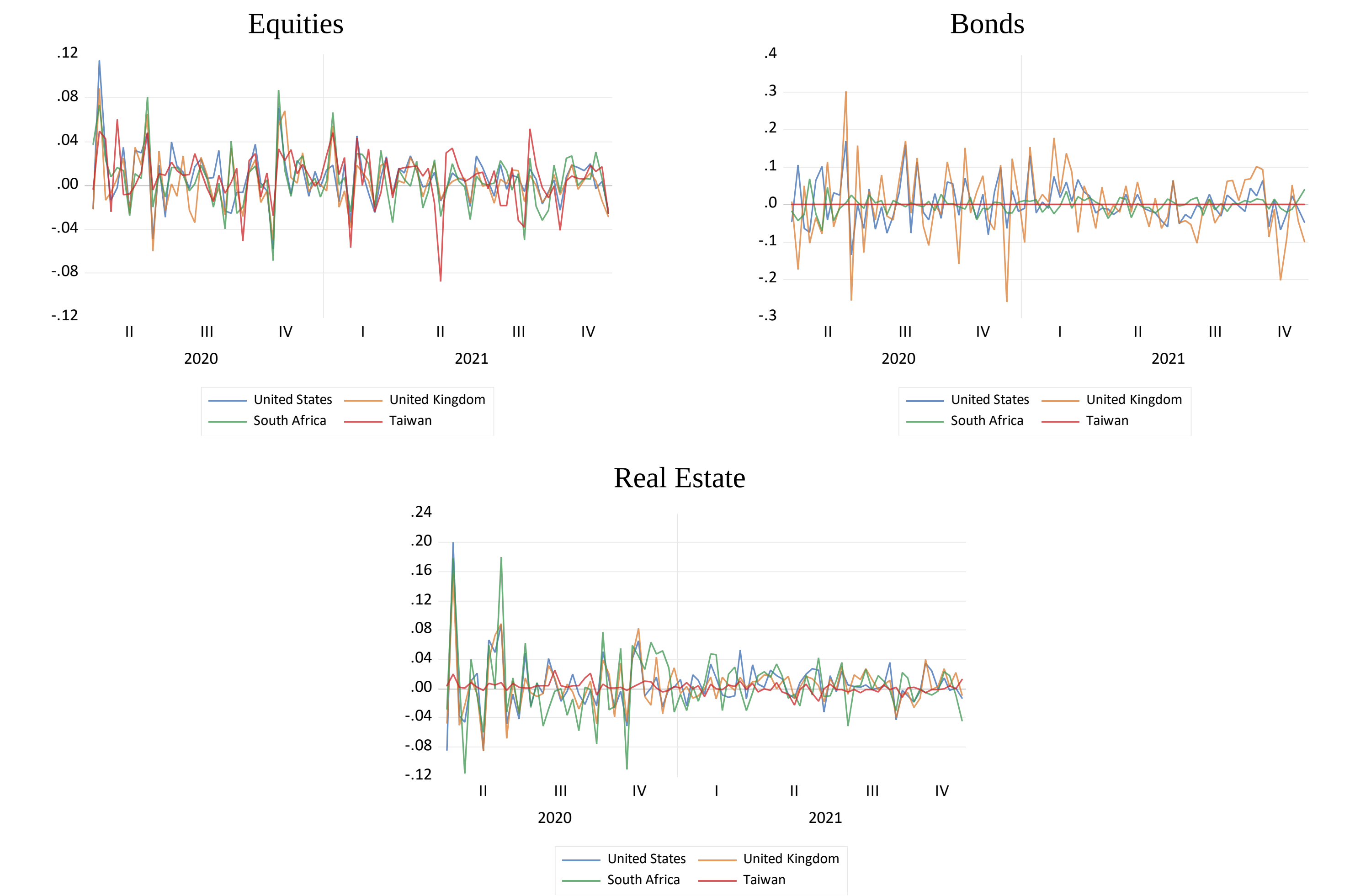


Table 4. 1: Out-of-Sample GARCH(1,1) Parameters

Panel A: Equities											
Country	α	β	λ	α+β	Standard error	σ_i	$\bar{\sigma}_t$	Durbin-Watson	Akaike Info Criterion	Schwarz Criterion	Hannan-Quinn Criterion
U.S.	0.00003***	0.52501***	0.40125***	0.52504	0.00017***	0.00388	0.16475	0.43837	-5.73662	-5.72664	-5.73298
UK	0.00007***	0.84943***	-0.01979***	0.8495	0.00017***	0.00305	0.00345	0.40544	-5.66243	-5.65245	-5.65879
TW	0.00008***	0.73901***	-0.02115***	0.73909	0.00032***	0.00476	0.00523	0.40396	-5.58808	-5.5781	-5.58444
SA	0.00009***	0.87573***	-0.02206**	0.87581	0.00016***	0.00182	0.00231	0.40514	-5.37335	-5.36337	-5.36971
Panel B: Bonds											
Country	α	β	λ	α+β	Standard error	σ_i	$\bar{\sigma}_t$	Durbin-Watson	Akaike Info Criterion	Schwarz Criterion	Hannan-Quinn Criterion
U.S.	0.00023***	0.90397***	-0.01707***	0.90419	0.00027***	-0.00324	-0.00293	0.45582	-4.28573	-4.27575	-4.28209
UK	0.00019***	0.24228***	0.78149***	0.24248	0.00044***	-0.00182	0.60821	0.48027	-3.57316	-3.56318	-3.56952
TW	0.00051***	0.65843**	-0.00084	0.65894	3.17E-04	0.00003	0.00003	0.39182	-6.94559	-6.93561	-6.94195
SA	0.00006***	0.88736***	-0.00994**	0.88742	0.00015	0.00012	0.00022	0.43916	-5.77733	-5.76735	-5.77369
Panel C: Listed Real Estate											
Country	α	β	λ	α+β	Standard error	σ_i	$\bar{\sigma}_t$	Durbin-Watson	Akaike Info Criterion	Schwarz Criterion	Hannan-Quinn Criterion
U.S.	0.00008***	0.91063***	-0.02634***	0.91071	0.00017***	0.00425	0.00497	0.46986	-5.38176	-5.37178	-5.37812
UK	0.00011***	0.80610***	-0.01116***	0.80621	0.00025***	0.00236	0.0025	0.4202	-5.1753	-5.16532	-5.17167
TW	0.00000***	1.38751***	-0.00239**	1.38752	3.33E-05***	-0.00002	-0.00001	0.49569	-12.61158	-12.6041	-12.60886
SA	0.00002**	0.32168**	0.65688**	0.3217	0.00024*	0.00044	0.43161	0.39307	-5.07711	-5.06713	-5.07348

Note: ***, ** and * illustrate significance at 1%, 5% and 10%, respectively. U.S. stands for the United States of America, the UK is for United Kingdom, TW is for Taiwan, SA is for South Africa, α captures the immediate impact of a shock on the current conditional variance (volatility), β captures the effect of past conditional variance (volatility) on the current conditional variance (volatility) , λ is a risk premium parameter, σ_i is spot volatility and $\bar{\sigma}_t$ long term average volatility. Just like Merkle (2018), $\bar{\sigma}_t$ is based on the variance formula in order to capture potential biasness in volatility.

Figure 4.1 illustrates that returns of the three indices across all four countries (i.e., The U.S., the UK, Taiwan, and South Africa) experienced patterns similar to volatility clustering patterns (See; Kola 2021), during the period of 2013-2021. Most of the spikes were mainly experienced in the equities markets. According to most market commentators, the COVID-19 global pandemic, commenced at the latter part of 2019. The corona virus outbreak of 2019 was proclaimed a global pandemic in March 2020. This announcement correlates with the sharp spikes (volatility) observed in early 2020 in figure 4.1 which continued until early 2021. China and the G7 recorded the most covid-19 cases and deaths (Akhtaruzzaman et al, 2021). The U.S. and UK markets which hold the biggest share of the global markets were significantly shaken by the COVID-19 outbreak (Akhtaruzzaman et al, 2021).

Table 4.1 presents the GARCH(1,1) parameters for the out-of-sample period (2020-2021). Although, the time series has 416 points, the parameters are statistically significant, which is encouraging to this point. For most time series data analysis, there should be at least 500 points for the GARCH(1,1) parameters to be statistically significant and for the model not to explode. The GARCH(1,1) parameters are appropriate when α and β add up to one (Kola 2021). This is true for all the indices across all four countries except for Taiwan's real estate index. When one contrasts the spot GARCH(1,1) volatilities (i.e., σ_i) with the long-term GARCH(1,1) volatilities (i.e., $\bar{\sigma}_t$), pretty much $\sigma_i < \bar{\sigma}_t$. Thus, when spot volatilities converge from the bottom (top) towards their long-term average volatilities, it implies bull (bear) market conditions (Marcato et al, 2018). Thus, the latter illustration confirms that the three indices of the four countries during 2013-2021, experienced bull market conditions, on average. It might be that certain constituents of those indices experienced bear market conditions but not the markets as illustrated by the indices.

Fundamentally, lambda (λ) is a risk premium parameter, a positive λ value is indicative of a positive relationship between returns and volatility (Kenc and Cevik, 2021). Put it simply, a rise in mean returns is a result of a rise in conditional variance which is a proxy for a rise in risk and vice versa. In table 4.1, three out of the twelve asset classes presented a positive lambda (U.S. equities, UK bonds and South African listed real estate) and the rest presented a negative lambda value.

The standard errors according to Merkle (2018), talk to the issue of systematic and idiosyncratic risks. This implies that the statistical significance of errors illustrates the presence of both risks (systematic and idiosyncratic) according to Merkle (2018). Moreover, he opines that positive error symbolises high presence of information asymmetry, which contributes to herding behaviour among investors. Hence, based on arguments from Merkle (2018), the presence of positive errors is unsurprising and implies herding behaviour within each index. The VAR calculations will further explore herding behaviour. According to Merkle (2018), when the adjusted R^2 value is small, it represents the availability of information asymmetry. On the other hand, Benefield et al. (2009) opined that the heterogenous nature of real estate leads to lower adjusted $R^r s$ in the real estate industry.

The Durbin-Watson values and diagnostic measures (Akaike, Schwartz and Hannan-Quinn) fall outside normal ranges; 1.3 and 1.6-2.7; respectively, which for Durbin-Watson shows the presence of autocorrelation and for the diagnostic measures, it implies skewed data (See; Kola 2021). The latter distribution might be due to the length of the time series.

4.5.1.2 In-Sample

Figure 4. 2: In-sample log returns

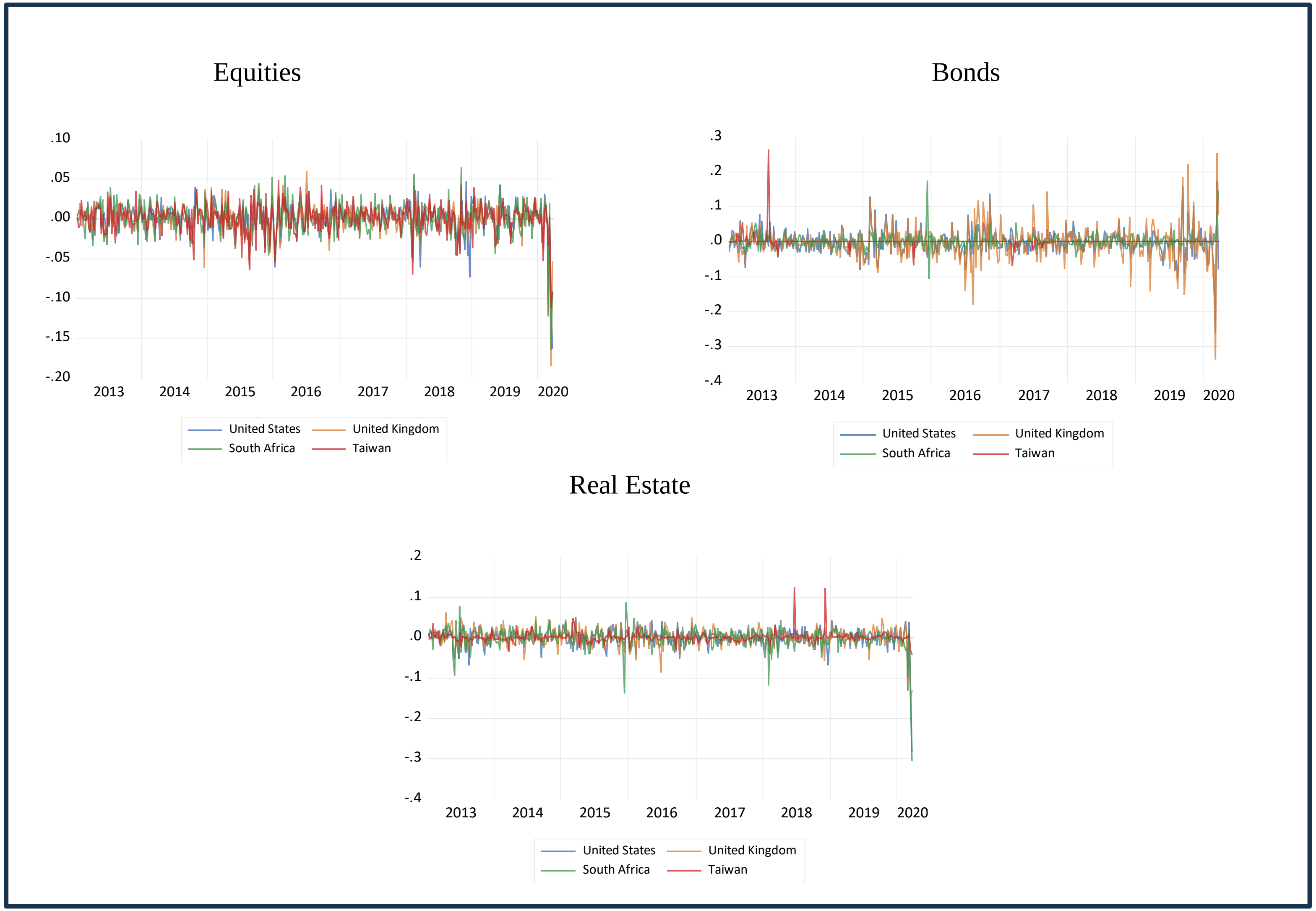


Table 4. 2: In-Sample GARCH(1,1) Parameters

Panel D: Equities											
Country	α	β	λ	α+β	Standard error	σ_i	$\bar{\sigma}_t$	Durbin-Watson	Akaike Info Criterion	Schwarz Criterion	Hannan-Quinn Criterion
U.S.	0.00002***	0.50878***	0.48542***	0.50879	0.00028***	0.00614	0.24152	0.43667	-5.56432	-5.54653	-5.5576
UK	0.00007***	0.96385***	-0.01681*	0.96392	0.00025***	0.00392	0.00422	0.39988	-5.54861	-5.53082	-5.54189
TW	0.00010***	0.80179***	-0.02298***	0.80189	0.00032***	0.00476	0.00532	0.39379	-5.4446	-5.4268	-5.43787
SA	0.00010***	0.92895***	-0.02421***	0.92905	0.00021***	0.00188	0.00248	0.39944	-5.20118	-5.18338	-5.19445
Panel E: Bonds											
Country	α	β	λ	α+β	Standard error	σ_i	$\bar{\sigma}_t$	Durbin-Watson	Akaike Info Criterion	Schwarz Criterion	Hannan-Quinn Criterion
U.S.	0.00026***	0.95768***	-0.01878***	0.95794	0.00045***	-0.00443	0.24152	0.46413	-4.06308	-4.04529	-4.05636
UK	0.00116***	0.76310***	-0.02563**	0.76426	0.00107	0.0007	0.00422	0.49834	-3.0023	-2.98451	-2.99558
TW	0.00000***	0.41202***	0.62754***	0.41202	1.11E-07***	0	0.00532	0.38356	-31.19133	-31.17353	-31.18461
SA	0.00005***	0.88152***	-0.03903***	0.88156	0.00020***	0.0026	0.00248	0.39263	-5.9256	-5.90781	-5.91888
Panel F: Listed Real Estate											
Country	α	β	λ	α+β	Standard error	σ_i	$\bar{\sigma}_t$	Durbin-Watson	Akaike Info Criterion	Schwarz Criterion	Hannan-Quinn Criterion
U.S.	0.00010***	0.88527***	-0.02470**	0.88537	0.00034***	0.00366	0.00429	0.49936	-5.15841	-5.14062	-5.15169
UK	0.00004***	0.40034***	0.52776***	0.40038	0.00034***	0.00196	0.28013	0.43261	-5.15076	-5.13297	-5.14404
TW	0	0.85344***	0.79688***	0.85344	2.17E-08***	0	0.63501	0.4674	-20.50567	-20.48788	-20.49895
SA	0.00019***	0.88410***	-0.00714	0.88429	0.00034***	-0.00264	-0.00258	0.37821	-4.75054	-4.73275	-4.74382

Note: ***, ** and * illustrate significance at 1%, 5% and 10%, respectively. U.S. stands for the United States of America, the UK is for United Kingdom, TW is for Taiwan, SA is for South Africa, α captures the immediate impact of a shock on the current conditional variance (volatility), β captures the effect of past conditional variance (volatility) on the current conditional variance (volatility) , λ is a risk premium parameter, σ_i is spot volatility and $\bar{\sigma}_t$ long term average volatility. Just like Merkle (2018), $\bar{\sigma}_t$ is based on the variance formula in order to capture potential biasness in volatility.

Figure 4.2 illustrates the same pattern as shown in figure 4.1. Notably, the spikes are more evident in figure 4. 2 than in figure 4.1-this is probably due to spacing in the graph (i.e., figure 4.1). Fundamentally, the same arguments made for figure 4.1, can be made for figure 4.2.

Table 4.2 presents the GARCH(1,1) parameters for the in-sample time series (between 2013 and 2020) and shows the same and/or similar pattern as the GARCH(1,1) parameters of the out-of-sample time series, including convergence of the norm-bull market conditions. The fact that in terms of findings for out-of-sampling (i.e., forecasting) and in-sampling (i.e., validation) confirm the same earlier findings that, confirms the strength of the parameters (Merkle, 2018).

4.5.2 The VAR(1,4) Results

In order to be consistent through the entire analysis in this study, the VAR analysis follows the same pattern and sequence as in the GARCH(1,1) analysis. The section starts with running preliminary deciding tests on the out-of-sample time series. First in terms of indices, it considers the equities, then bonds and finally listed real estate. The pattern of the analysis is the U.S., the UK, Taiwan and South Africa. This is because of the earlier reasons listed under the GARCH(1,1) analysis. The common tests used to decide the lag length are as follows. First is the residual test, which takes one to the autocorrelation LM test. Results based on up to two lags illustrate that, in the two lags, there is autocorrelation; hence, using those two lags might not capture all the dynamism in the time series. Thereafter, the study proceeds to the second test, which is on deciding what lag order to use. Thus, from the lag structure, using the lag length criteria test, up to the 4^{th} lag, and the results based on the Akaike criterion and Schwartz, show that lags 4 and 1 are appropriate. However, in the LM test, lag 1 has already been rejected. Note that for the second test on deciding what lag order to use, Hannan-Quinn criterion give the same results. Then, the study proceeds to the third test, which is on stationarity. Thus, from the lag structure, the AR roots table test is selected to detect test stationarity. Then, looking at the absolute modulus values, one can see that they are all less than one. Thus, there is stationarity in all those modulus values. Hence, the VAR calculations adopts lag 4; hence, the usage of VAR(1,4). Finally, the same procedure is carried on the in-sample time series following the same earlier sequential tests as in the out-of-sample time series. The results confirm the same finding as on the out-of-sample time series; thus, support using the VAR(1,4) model.

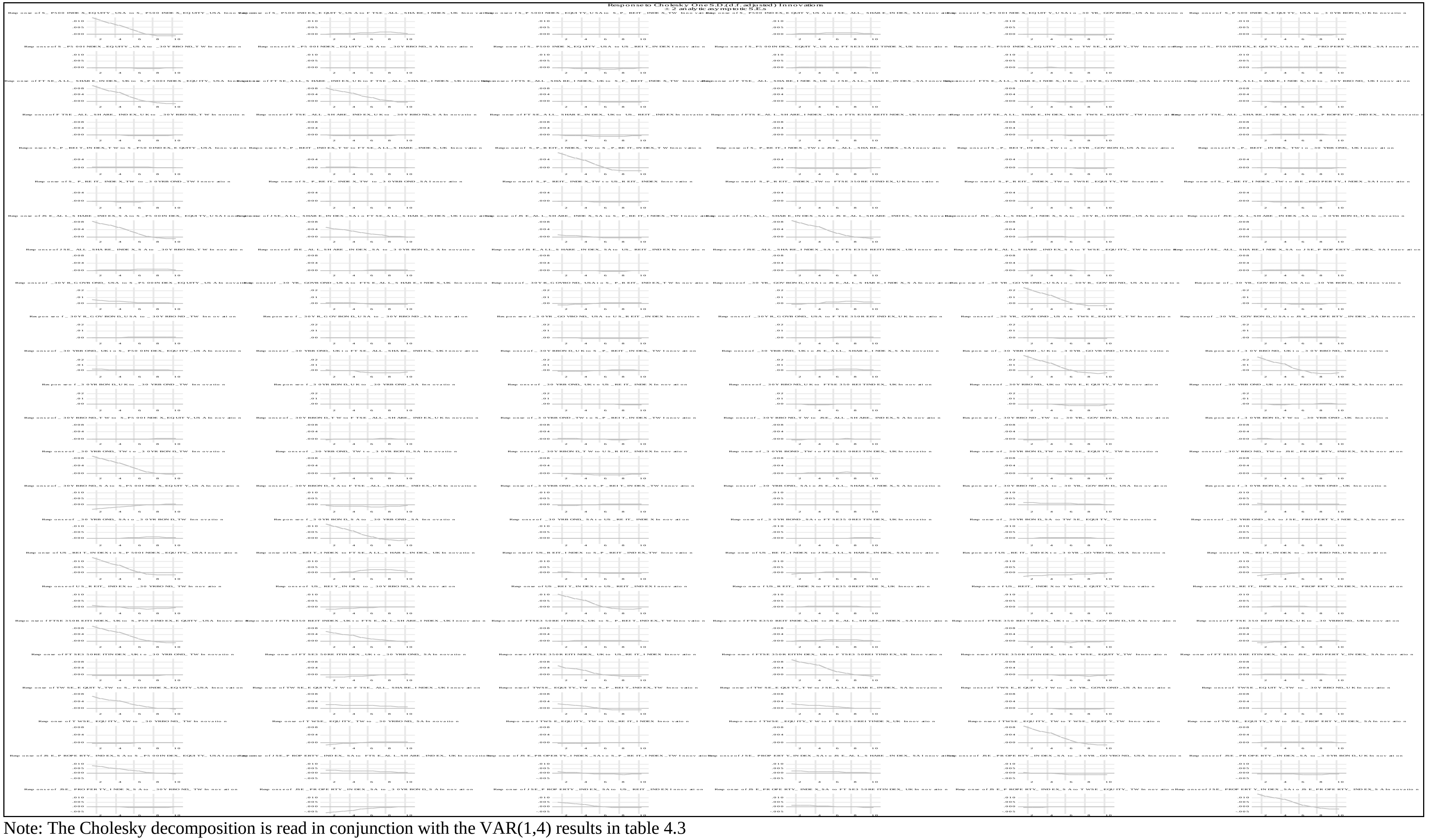
4.5.2.1 Out-of-Sample

Prior to running the multivariate VAR model, it is important to determine the appropriate number of lags. Firstly, the residual test is performed on the data to ensure that the data is within 2 standard error number. Thereafter, the residuals autocorrelation test confirms whether residuals are correlated or not, the p value needs to be greater than 0.05 which confirms that there is no serial correlation. Finally, the lag structure test is performed to find out the lag length criteria, the results show that Akaike AIC, Schwartz SC and Hannan-Quinn are statistically significant for four lags.

The variables are ordered by the size of the economy and liquidity of the market. The pattern of the analysis, it is still the same as before in section 4.5.2. The above order is based on the GDP of each country. The indices are ordered according to their liquidity, the most liquid index being equities, followed by bonds and lastly, listed real estate.

The results of Cholesky decomposition and VAR (1,4) for both in-sample and out-of-sample periods, are read jointly, i.e., for the graph and table. Kola (2021) illustrated the same interpretation process because it provides more insight about the results and offers better interpretation of the results (Kola 2021).

Figure 4. 3: Out-of-sample Cholesky Decomposition



Note: The Cholesky decomposition is read in conjunction with the VAR(1,4) results in table 4.3

Table 4. 3: Out-of-sample VAR(1,4)

Parameters	U.S. Equity Index	UK Equity Index	Taiwan Equity Index	SA Equity Index	U.S. 30yr Bond	UK 30yr Bond	Taiwan 30yr Bond	SA 30yr Bond	U.S. REIT Index	UK REIT Index	Taiwan REIT Index	SA REIT Index
U.S. Equity Index(-1)	0.826402 (0.04342) [19.0317]#	-0.005875 (0.04133) [-0.14217]	0.002763 (0.04024) [0.06867]	0.009983 (0.04506) [0.22153]	0.011670 (0.08710) [0.13399]	-0.023650 (0.12867) [-0.18381]	0.013836 (0.03040) [0.45513]	0.003087 (0.04250) [0.07262]	-0.018142 (0.05899) [-0.30756]	0.015253 (0.05247) [0.29068]	0.008571 (0.02343) [0.36578]	0.000884 (0.06173) [0.01432]
U.S. Equity Index(-2)	-6.30E-17 (0.05698) [-1.1e-15]	-9.84E-17 (0.05423) [-1.8e-15]	1.10E-16 (0.05280) [2.1e-15]	-2.48E-17 (0.05913) [-4.2e-16]	-4.15E-17 (0.11429) [-3.6e-16]	-7.91E-16 (0.16884) [-4.7e-15]	-2.71E-17 (0.03989) [-6.8e-16]	1.91E-17 (0.05577) [3.4e-16]	1.44E-16 (0.07740) [1.9e-15]	-2.33E-17 (0.06885) [-3.4e-16]	-5.30E-17 (0.03075) [-1.7e-15]	-2.94E-16 (0.08100) [-3.6e-15]
U.S. Equity Index(-3)	1.54E-16 (0.05698) [2.7e-15]	1.65E-16 (0.05423) [3.1e-15]	-8.78E-17 (0.05280) [-1.7e-15]	-8.73E-17 (0.05913) [-1.5e-15]	-1.81E-17 (0.11429) [-1.6e-16]	3.00E-16 (0.16884) [1.8e-15]	1.47E-18 (0.03989) [3.7e-17]	-1.44E-16 (0.05577) [-2.6e-15]	-3.17E-16 (0.07740) [-4.1e-15]	-1.63E-16 (0.06885) [-2.4e-15]	-3.41E-17 (0.03075) [-1.1e-15]	7.88E-17 (0.08100) [9.7e-16]
U.S. Equity Index(-4)	-0.173548 (0.04354) [-3.98549]#	-0.002658 (0.04144) [-0.06415]	-0.019773 (0.04035) [-0.49000]	-0.018118 (0.04519) [-0.40093]	0.177087 (0.08734) [2.02745]#	0.291118 (0.12903) [2.25619]#	0.025415 (0.03049) [0.83367]	0.063115 (0.04262) [1.48073]	-0.056857 (0.05915) [-0.96120]	0.020061 (0.05262) [0.38123]	0.014313 (0.02350) [0.60912]	-0.035603 (0.06190) [-0.57512]
UK Equity Index(-1)	-9.77E-05 (0.04368) [-0.00224]	0.850822 (0.04157) [20.4688]#	0.014282 (0.04047) [0.35287]	-0.010086 (0.04532) [-0.22252]	-0.008725 (0.08761) [-0.09960]	-0.035768 (0.12942) [-0.27638]	-0.009505 (0.03058) [-0.31086]	-0.032714 (0.04275) [-0.76522]	0.014775 (0.05933) [0.24903]	-0.012269 (0.05278) [-0.23246]	0.000854 (0.02357) [0.03623]	0.021833 (0.06209) [0.35164]
UK Equity Index(-2)	1.81E-16 (0.05783) [3.1e-15]	-2.26E-17 (0.05504) [-4.1e-16]	-7.50E-18 (0.05359) [-1.4e-16]	-5.68E-17 (0.06002) [-9.5e-16]	4.43E-17 (0.11600) [3.8e-16]	7.49E-16 (0.17136) [4.4e-15]	-1.88E-17 (0.04049) [-4.7e-16]	-6.01E-17 (0.05661) [-1.1e-15]	-1.23E-16 (0.07856) [-1.6e-15]	8.54E-17 (0.06988) [1.2e-15]	4.31E-18 (0.03121) [1.4e-16]	2.33E-16 (0.08221) [2.8e-15]
UK Equity Index(-3)	-8.55E-17 (0.05783) [-1.5e-15]	-1.23E-16 (0.05504) [-2.2e-15]	-3.02E-17 (0.05359) [-5.6e-16]	6.55E-17 (0.06002) [1.1e-15]	-2.29E-17 (0.11600) [-2.0e-16]	-3.20E-16 (0.17136) [-1.9e-15]	1.04E-17 (0.04049) [2.6e-16]	7.69E-17 (0.05661) [1.4e-15]	4.25E-16 (0.07856) [5.4e-15]	1.22E-16 (0.06988) [1.7e-15]	-6.94E-18 (0.03121) [-2.2e-16]	6.25E-17 (0.08221) [7.6e-16]
UK Equity Index(-4)	0.037722 (0.04391) [0.85906]	-0.114510 (0.04179) [-2.74005]#	0.073891 (0.04069) [1.81582]	0.046394 (0.04557) [1.01808]	-0.182504 (0.08808) [-2.07205]#	-0.321790 (0.13012) [-2.47312]#	0.008801 (0.03074) [0.28628]	-0.092108 (0.04298) [-2.14292] #	0.113236 (0.05965) [1.89838]	0.009637 (0.05306) [0.18161]	0.016126 (0.02370) [0.68054]	0.043328 (0.06242) [0.69409]
Taiwan Equity Index(-1)	0.011075 (0.03026) [0.36605]	0.012648 (0.02879) [0.43925]	0.835685 (0.02804) [29.8055]#	0.012913 (0.03140) [0.41128]	-0.011611 (0.06069) [-0.19133]	-0.007410 (0.08965) [-0.08265]	-0.006552 (0.02118) [-0.30932]	0.011900 (0.02962) [0.40181]	0.012430 (0.04110) [0.30243]	0.000465 (0.03656) [0.01272]	-0.003098 (0.01633) [-0.18976]	0.010093 (0.04301) [0.23466]
Taiwan Equity Index(-2)	4.50E-17 (0.03958) [1.1e-15]	2.00E-17 (0.03767) [5.3e-16]	1.20E-17 (0.03668) [3.3e-16]	4.63E-17 (0.04108) [1.1e-15]	1.45E-16 (0.07939) [1.8e-15]	6.51E-17 (0.11728) [5.5e-16]	2.06E-17 (0.02771) [7.4e-16]	-3.33E-17 (0.03874) [-8.6e-16]	-4.59E-17 (0.05377) [-8.5e-16]	9.38E-18 (0.04783) [2.0e-16]	-8.81E-18 (0.02136) [-4.1e-16]	1.05E-17 (0.05627) [1.9e-16]
Taiwan Equity Index(-3)	1.53E-17 (0.03958) [3.9e-16]	-3.42E-18 (0.03767) [-9.1e-17]	-3.54E-17 (0.03668) [-9.7e-16]	1.45E-17 (0.04108) [3.5e-16]	-1.58E-16 (0.07939) [-2.0e-15]	1.27E-17 (0.11728) [1.1e-16]	-8.41E-18 (0.02771) [-3.0e-16]	7.20E-17 (0.03874) [1.9e-15]	9.39E-17 (0.05377) [1.7e-15]	-5.65E-17 (0.04783) [-1.2e-15]	2.00E-17 (0.02136) [9.4e-16]	-1.26E-17 (0.05627) [-2.2e-16]
Taiwan Equity Index(-4)	-0.015919 (0.03025) [-0.52617]	-0.029790 (0.02879) [-1.03463]	-0.171502 (0.02804) [-6.11711]#	-0.010325 (0.03140) [-0.32887]	-0.071968 (0.06068) [-1.18593]	-0.145091 (0.08965) [-1.61848]	-0.014293 (0.02118) [-0.67481]	0.005097 (0.02961) [0.17212]	-0.007211 (0.04110) [-0.17546]	-0.046761 (0.03656) [-1.27904]	0.000854 (0.01633) [0.05230]	0.001163 (0.04301) [0.02705]
SA Equity Index(-1)	0.016893 (0.03269) [0.51683]	-0.000328 (0.03111) [-0.01055]	0.006301 (0.03029) [0.20802]	0.843615 (0.03392) [24.8700]#	0.058071 (0.06556) [0.88571]	0.073842 (0.09686) [0.76239]	0.014246 (0.02288) [0.62254]	0.006881 (0.03200) [0.21507]	0.011867 (0.04440) [0.26727]	0.008965 (0.03950) [0.22696]	-0.005998 (0.01764) [-0.34003]	0.009397 (0.04647) [0.20222]
SA Equity	-9.06E-17	1.30E-16	-8.32E-17	-2.68E-17	-9.30E-17	-1.60E-16	1.85E-17	-5.45E-17	8.29E-17	-1.04E-16	3.80E-17	-3.19E-18

Index(-2)	(0.04296)	(0.04089)	(0.03981)	(0.04459)	(0.08618)	(0.12731)	(0.03008)	(0.04205)	(0.05836)	(0.05192)	(0.02318)	(0.06108)
	[-2.1e-15]	[3.2e-15]	[-2.1e-15]	[-6.0e-16]	[-1.1e-15]	[-1.3e-15]	[6.2e-16]	[-1.3e-15]	[1.4e-15]	[-2.0e-15]	[1.6e-15]	[-5.2e-17]
SA Equity Index(-3)	1.04E-17	-2.92E-17	9.14E-17	4.65E-17	1.72E-16	2.78E-18	-5.08E-18	6.01E-17	-1.77E-16	9.88E-17	1.47E-17	-8.66E-17
	(0.04296)	(0.04089)	(0.03981)	(0.04459)	(0.08618)	(0.12731)	(0.03008)	(0.04205)	(0.05836)	(0.05192)	(0.02318)	(0.06108)
	[2.4e-16]	[-7.1e-16]	[2.3e-15]	[1.0e-15]	[2.0e-15]	[2.2e-17]	[-1.7e-16]	[1.4e-15]	[-3.0e-15]	[1.9e-15]	[6.3e-16]	[-1.4e-15]
SA Equity Index(-4)	0.035932	0.006110	0.014588	-0.144495	0.129622	0.131118	0.003238	-0.010467	0.032329	0.038063	-0.008047	0.064619
	(0.03276)	(0.03118)	(0.03036)	(0.03400)	(0.06572)	(0.09708)	(0.02294)	(0.03207)	(0.04450)	(0.03959)	(0.01768)	(0.04658)
	[1.09677]	[0.19596]	[0.48049]	[-4.24992]#	[1.97246]	[1.35063]	[0.14116]	[-0.32638]	[0.72643]	[0.96142]	[-0.45516]	[1.38740]
U.S. 30yr Bond(-1)	-0.002082	0.002127	-0.001265	0.007929	0.822028	0.014390	0.002697	0.002430	-0.019616	-0.007328	0.002602	-0.002249
	(0.01587)	(0.01510)	(0.01471)	(0.01647)	(0.03183)	(0.04702)	(0.01111)	(0.01553)	(0.02156)	(0.01918)	(0.00856)	(0.02256)
	[-0.13117]	[0.14082]	[-0.08601]	[0.48145]	[25.8234]#	[0.30600]	[0.24273]	[0.15643]	[-0.90993]	[-0.38209]	[0.30386]	[-0.09968]
U.S. 30yr Bond(-2)	-1.32E-17	-1.13E-17	2.29E-17	-8.24E-18	-2.50E-17	3.05E-18	-9.14E-18	-4.22E-19	-2.93E-17	-7.41E-17	9.87E-18	2.95E-17
	(0.02065)	(0.01965)	(0.01913)	(0.02143)	(0.04141)	(0.06118)	(0.01445)	(0.02021)	(0.02805)	(0.02495)	(0.01114)	(0.02935)
	[-6.4e-16]	[-5.8e-16]	[1.2e-15]	[-3.8e-16]	[-6.0e-16]	[5.0e-17]	[-6.3e-16]	[-2.1e-17]	[-1.0e-15]	[-3.0e-15]	[8.9e-16]	[1.0e-15]
U.S. 30yr Bond(-3)	9.76E-18	-4.69E-18	1.12E-17	3.51E-17	-1.56E-17	-5.94E-17	-8.28E-19	3.08E-18	-3.09E-18	1.01E-16	-2.92E-18	-9.74E-17
	(0.02065)	(0.01965)	(0.01913)	(0.02143)	(0.04141)	(0.06118)	(0.01445)	(0.02021)	(0.02805)	(0.02495)	(0.01114)	(0.02935)
	[4.7e-16]	[-2.4e-16]	[5.9e-16]	[1.6e-15]	[-3.8e-16]	[-9.7e-16]	[-5.7e-17]	[1.5e-16]	[-1.1e-16]	[4.0e-15]	[-2.6e-16]	[-3.3e-15]
U.S. 30y Bond(-4)	-0.013372	-0.006786	-0.011403	-0.006864	-0.176568	0.011234	-0.002529	-6.98E-05	-0.031367	-0.017852	-1.39E-05	-0.008746
	(0.01584)	(0.01507)	(0.01468)	(0.01643)	(0.03177)	(0.04693)	(0.01109)	(0.01550)	(0.02151)	(0.01914)	(0.00855)	(0.02251)
	[-0.84437]	[-0.45026]	[-0.77698]	[-0.41767]	[-5.55845]#	[0.23940]	[-0.22812]	[-0.00450]	[-1.45807]	[-0.93285]	[-0.00163]	[-0.38846]
UK 30yr Bond(-1)	-0.004552	-0.005176	-0.002715	-0.004305	-0.013522	0.794440	-0.003295	0.002758	0.005540	-0.002283	-0.001504	-0.006511
	(0.01060)	(0.01009)	(0.00982)	(0.01100)	(0.02127)	(0.03141)	(0.00742)	(0.01038)	(0.01440)	(0.01281)	(0.00572)	(0.01507)
	[-0.42940]	[-0.51298]	[-0.27632]	[-0.39131]	[-0.63588]	[25.2886]#	[-0.44389]	[0.26575]	[0.38471]	[-0.17823]	[-0.26296]	[-0.43197]
UK 30yr Bond(-2)	1.17E-17	8.17E-18	-2.01E-17	-6.94E-18	-1.48E-17	1.34E-17	7.56E-18	2.51E-18	7.30E-18	6.22E-17	-1.64E-18	7.06E-18
	(0.01378)	(0.01312)	(0.01277)	(0.01430)	(0.02765)	(0.04084)	(0.00965)	(0.01349)	(0.01872)	(0.01666)	(0.00744)	(0.01959)
	[8.5e-16]	[6.2e-16]	[-1.6e-15]	[-4.9e-16]	[-5.3e-16]	[3.3e-16]	[7.8e-16]	[1.9e-16]	[3.9e-16]	[3.7e-15]	[-2.2e-16]	[3.6e-16]
UK 30yr Bond(-3)	-2.04E-17	-8.83E-18	5.65E-18	5.41E-18	-2.66E-18	5.84E-17	9.23E-19	2.88E-18	3.81E-18	-6.03E-17	1.46E-19	4.13E-17
	(0.01378)	(0.01312)	(0.01277)	(0.01430)	(0.02765)	(0.04084)	(0.00965)	(0.01349)	(0.01872)	(0.01666)	(0.00744)	(0.01959)
	[-1.5e-15]	[-6.7e-16]	[4.4e-16]	[3.8e-16]	[-9.6e-17]	[1.4e-15]	[9.6e-17]	[2.1e-16]	[2.0e-16]	[-3.6e-15]	[2.0e-17]	[2.1e-15]
UK 30yr Bond(-4)	-0.009981	-0.001915	0.001529	-0.001048	-0.013813	-0.201656	-0.001958	0.009910	-0.002932	0.000496	-0.002883	-0.013999
	(0.01062)	(0.01011)	(0.00984)	(0.01102)	(0.02131)	(0.03148)	(0.00744)	(0.01040)	(0.01443)	(0.01284)	(0.00573)	(0.01510)
	[-0.93960]	[-0.18947]	[0.15535]	[-0.09503]	[-0.64826]	[-6.40667]#	[-0.26327]	[0.95307]	[-0.20319]	[0.03860]	[-0.50298]	[-0.92704]
Taiwan 30yr Bond(-1)	-0.003299	-0.001170	-0.007775	0.013270	0.010938	0.004440	0.860084	0.014281	-0.033454	-0.005448	-0.002187	-0.011607
	(0.03039)	(0.02892)	(0.02816)	(0.03154)	(0.06096)	(0.09005)	(0.02128)	(0.02975)	(0.04128)	(0.03672)	(0.01640)	(0.04320)
	[-0.10857]	[-0.04046]	[-0.27608]	[0.42075]	[0.17943]	[0.04930]	[40.4237]#	[0.48007]	[-0.81036]	[-0.14833]	[-0.13335]	[-0.26866]
Taiwan 30yr Bond(-2)	-1.19E-18	-1.39E-19	2.08E-17	3.25E-17	-3.62E-17	-1.09E-16	-1.02E-17	-7.78E-18	4.98E-17	-2.90E-17	-8.88E-18	-2.26E-17
	(0.04035)	(0.03840)	(0.03739)	(0.04187)	(0.08093)	(0.11956)	(0.02825)	(0.03949)	(0.05481)	(0.04876)	(0.02177)	(0.05736)
	[-2.9e-17]	[-3.6e-18]	[5.6e-16]	[7.8e-16]	[-4.5e-16]	[-9.1e-16]	[-3.6e-16]	[-2.0e-16]	[9.1e-16]	[-5.9e-16]	[-4.1e-16]	[-3.9e-16]
Taiwan 30yr Bond(-3)	1.34E-17	2.66E-17	-9.00E-18	-2.41E-17	7.26E-17	-1.10E-17	-7.14E-17	-6.52E-18	-9.60E-19	-1.14E-17	6.02E-18	-1.81E-17
	(0.04035)	(0.03840)	(0.03739)	(0.04187)	(0.08093)	(0.11956)	(0.02825)	(0.03949)	(0.05481)	(0.04876)	(0.02177)	(0.05736)
	[3.3e-16]	[6.9e-16]	[-2.4e-16]	[-5.8e-16]	[9.0e-16]	[-9.2e-17]	[-2.5e-15]	[-1.7e-16]	[-1.8e-17]	[-2.3e-16]	[2.8e-16]	[-3.2e-16]
Taiwan 30yr	-0.025652	-0.015710	-0.001398	0.011990	0.036606	0.012373	-0.139465	0.032322	-0.052991	-0.021327	0.000226	-0.004835

Bond(-4)	(0.03042) [-0.84317]	(0.02895) [-0.54258]	(0.02819) [-0.04957]	(0.03157) [0.37975]	(0.06103) [0.59986]	(0.09015) [0.13725]	(0.02130) [-6.54770]#	(0.02978) [1.08536]	(0.04133) [-1.28222]	(0.03676) [-0.58010]	(0.01642) [0.01378]	(0.04325) [-0.11180]
SA 30yr Bond(-1)	-0.001182 (0.02452) [-0.04820]	-0.008715 (0.02334) [-0.37345]	0.012466 (0.02272) [0.54859]	0.000635 (0.02545) [0.02496]	-6.58E-05 (0.04919) [-0.00134]	0.013556 (0.07266) [0.18657]	0.004561 (0.01717) [0.26570]	0.811841 (0.02400) [33.8231]#	-0.004670 (0.03331) [-0.14020]	-0.009859 (0.02963) [-0.33270]	0.001281 (0.01323) [0.09684]	-0.003321 (0.03486) [-0.09525]
SA 30yr Bond(-2)	-3.58E-17 (0.03182) [-1.1e-15]	-2.15E-18 (0.03029) [-7.1e-17]	-1.21E-17 (0.02949) [-4.1e-16]	2.07E-17 (0.03302) [6.3e-16]	7.31E-17 (0.06383) [1.1e-15]	-4.15E-17 (0.09430) [-4.4e-16]	2.54E-17 (0.02228) [1.1e-15]	-1.35E-17 (0.03115) [-4.3e-16]	-6.62E-18 (0.04323) [-1.5e-16]	-2.92E-17 (0.03846) [-7.6e-16]	-4.63E-18 (0.01717) [-2.7e-16]	6.53E-17 (0.04524) [1.4e-15]
SA 30yr Bond(-3)	-3.24E-17 (0.03182) [-1.0e-15]	-1.75E-17 (0.03029) [-5.8e-16]	-3.16E-17 (0.02949) [-1.1e-15]	-6.48E-17 (0.03302) [-2.0e-15]	-8.09E-17 (0.06383) [-1.3e-15]	4.80E-17 (0.09430) [5.1e-16]	-4.14E-18 (0.02228) [-1.9e-16]	-8.85E-18 (0.03115) [-2.8e-16]	2.94E-17 (0.04323) [6.8e-16]	-3.10E-17 (0.03846) [-8.1e-16]	7.50E-18 (0.01717) [4.4e-16]	-4.45E-18 (0.04524) [-9.8e-17]
SA 30yr Bond(-4)	-0.008487 (0.02448) [-0.34668]	-0.004500 (0.02330) [-0.19316]	0.015127 (0.02269) [0.66680]	0.003697 (0.02540) [0.14553]	0.003759 (0.04910) [0.07654]	-0.019181 (0.07254) [-0.26442]	-0.002932 (0.01714) [-0.17108]	-0.179792 (0.02396) [-7.50315]#	-0.005322 (0.03325) [-0.16005]	-0.009992 (0.02958) [-0.33779]	0.004275 (0.01321) [0.32361]	-0.019211 (0.03480) [-0.55201]
U.S. REIT Index(-1)	-0.043613 (0.02920) [-1.49372]	-0.018783 (0.02779) [-0.67595]	-0.011896 (0.02706) [-0.43966]	-0.015014 (0.03030) [-0.49552]	-0.036563 (0.05857) [-0.62430]	0.029760 (0.08652) [0.34398]	-0.026375 (0.02044) [-1.29026]	0.013846 (0.02858) [0.48447]	0.766045 (0.03966) [19.3143]#	-0.031952 (0.03528) [-0.90558]	-0.006282 (0.01576) [-0.39873]	-0.031340 (0.04151) [-0.75503]
U.S. REIT Index(-2)	4.49E-17 (0.03811) [1.2e-15]	7.30E-17 (0.03627) [2.0e-15]	-7.87E-17 (0.03531) [-2.2e-15]	8.30E-18 (0.03955) [2.1e-16]	1.21E-16 (0.07644) [1.6e-15]	4.60E-16 (0.11291) [4.1e-15]	4.65E-17 (0.02668) [1.7e-15]	-3.26E-17 (0.03730) [-8.7e-16]	-1.95E-16 (0.05176) [-3.8e-15]	4.64E-17 (0.04605) [1.0e-15]	4.69E-17 (0.02056) [2.3e-15]	2.21E-16 (0.05417) [4.1e-15]
U.S. REIT Index(-3)	-1.02E-16 (0.03811) [-2.7e-15]	-1.52E-16 (0.03627) [-4.2e-15]	2.74E-17 (0.03531) [7.7e-16]	3.34E-17 (0.03955) [8.4e-16]	-1.83E-16 (0.07644) [-2.4e-15]	-1.26E-16 (0.11291) [-1.1e-15]	3.95E-17 (0.02668) [1.5e-15]	6.14E-17 (0.03730) [1.6e-15]	1.54E-16 (0.05176) [3.0e-15]	7.24E-17 (0.04605) [1.6e-15]	-2.98E-18 (0.02056) [-1.4e-16]	-8.32E-17 (0.05417) [-1.5e-15]
U.S. REIT Index(-4)	-0.045005 (0.02922) [-1.54026]	-0.031044 (0.02781) [-1.11635]	-0.002908 (0.02708) [-0.10739]	-0.005535 (0.03032) [-0.18254]	-0.086418 (0.05861) [-1.47445]	-0.048754 (0.08658) [-0.56310]	-0.027341 (0.02046) [-1.33652]	-0.019607 (0.02860) [-0.68552]	-0.220330 (0.03969) [-5.55102]#	-0.038749 (0.03531) [-1.09740]	-0.003716 (0.01577) [-0.23564]	-0.002702 (0.04154) [-0.06506]
UK REIT Index(-1)	0.016943 (0.02894) [0.58541]	-0.005391 (0.02755) [-0.19571]	-0.002320 (0.02682) [-0.08651]	0.003544 (0.03004) [0.11801]	-0.012538 (0.05805) [-0.21597]	-0.028286 (0.08576) [-0.32982]	0.013573 (0.02026) [0.66986]	-0.009043 (0.02833) [-0.31918]	0.028584 (0.03932) [0.72703]	0.847063 (0.03497) [24.2191]#	0.010408 (0.01562) [0.66638]	0.013598 (0.04115) [0.33050]
UK REIT Index(-2)	-3.13E-17 (0.03809) [-8.2e-16]	-5.20E-17 (0.03625) [-1.4e-15]	4.02E-17 (0.03530) [1.1e-15]	9.55E-17 (0.03953) [2.4e-15]	-1.41E-16 (0.07641) [-1.8e-15]	-3.14E-16 (0.11287) [-2.8e-15]	-2.85E-17 (0.02667) [-1.1e-15]	7.37E-17 (0.03729) [2.0e-15]	1.12E-16 (0.05174) [2.2e-15]	-4.96E-17 (0.04603) [-1.1e-15]	-2.71E-17 (0.02056) [-1.3e-15]	-1.23E-16 (0.05415) [-2.3e-15]
UK REIT Index(-3)	-1.78E-17 (0.03809) [-4.7e-16]	9.23E-17 (0.03625) [2.5e-15]	-4.72E-18 (0.03530) [-1.3e-16]	-6.57E-17 (0.03953) [-1.7e-15]	1.55E-16 (0.07641) [2.0e-15]	1.57E-16 (0.11287) [1.4e-15]	-3.32E-17 (0.02667) [-1.2e-15]	-6.58E-17 (0.03729) [-1.8e-15]	-9.42E-17 (0.05174) [-1.8e-15]	-6.42E-17 (0.04603) [-1.4e-15]	1.94E-17 (0.02056) [9.4e-16]	-4.35E-17 (0.05415) [-8.0e-16]
UK REIT Index(-4)	0.013398 (0.02887) [0.46411]	0.003446 (0.02747) [0.12541]	-0.002518 (0.02675) [-0.09411]	-0.006537 (0.02996) [-0.21820]	0.034806 (0.05791) [0.60108]	0.018905 (0.08554) [0.22101]	0.018699 (0.02021) [0.92521]	0.007840 (0.02826) [0.27743]	0.024890 (0.03921) [0.63472]	-0.140175 (0.03489) [-4.01819]#	-0.001499 (0.01558) [-0.09625]	0.009252 (0.04104) [0.22544]
Taiwan REIT Index(-1)	-0.002248 (0.04070) [-0.05523]	-0.006430 (0.03874) [-0.16600]	-0.024089 (0.03772) [-0.63864]	-0.022332 (0.04224) [-0.52871]	0.030113 (0.08164) [0.36883]	0.010357 (0.12061) [0.08588]	-0.005986 (0.02850) [-0.21006]	0.010151 (0.03984) [0.25478]	-0.013283 (0.05529) [-0.24025]	0.011712 (0.04919) [0.23811]	0.802612 (0.02196) [36.5414]#	-0.036432 (0.05786) [-0.62961]
Taiwan REIT	-1.65E-17	-6.62E-17	3.13E-17	-3.07E-17	-1.24E-16	-8.37E-17	-1.60E-17	6.00E-18	8.42E-18	3.83E-18	1.90E-17	3.19E-17

Index(-2)	(0.05280) [-3.1e-16]	(0.05026) [-1.3e-15]	(0.04893) [6.4e-16]	(0.05480) [-5.6e-16]	(0.10592) [-1.2e-15]	(0.15647) [-5.3e-16]	(0.03697) [-4.3e-16]	(0.05169) [1.2e-16]	(0.07173) [1.2e-16]	(0.06381) [6.0e-17]	(0.02850) [6.7e-16]	(0.07507) [4.2e-16]
Taiwan REIT Index(-3)	2.33E-17 (0.05280) [4.4e-16]	2.24E-17 (0.05026) [4.5e-16]	-1.14E-18 (0.04893) [-2.3e-17]	3.83E-18 (0.05480) [7.0e-17]	6.49E-17 (0.10592) [6.1e-16]	7.33E-17 (0.15647) [4.7e-16]	-5.33E-18 (0.03697) [-1.4e-16]	-6.18E-17 (0.05169) [-1.2e-15]	-3.96E-17 (0.07173) [-5.5e-16]	4.04E-17 (0.06381) [6.3e-16]	-2.35E-17 (0.02850) [-8.2e-16]	-5.90E-17 (0.07507) [-7.9e-16]
Taiwan REIT Index(-4)	-0.022793 (0.04076) [-0.55913]	-0.006121 (0.03880) [-0.15778]	-0.038301 (0.03778) [-1.01386]	-0.030136 (0.04230) [-0.71235]	0.074434 (0.08177) [0.91030]	0.104577 (0.12079) [0.86575]	-0.006447 (0.02854) [-0.22588]	0.014694 (0.03990) [0.36824]	-0.033933 (0.05538) [-0.61278]	0.029046 (0.04926) [0.58964]	-0.200288 (0.02200) [-9.10475]#	-0.051593 (0.05795) [-0.89026]
SA REIT Index(-1)	0.015281 (0.01979) [0.77219]	0.016254 (0.01883) [0.86301]	0.013154 (0.01834) [0.71727]	0.013862 (0.02054) [0.67496]	0.004193 (0.03969) [0.10564]	-0.016052 (0.05864) [-0.27375]	-0.000621 (0.01385) [-0.04484]	-0.013154 (0.01937) [-0.67907]	0.019182 (0.02688) [0.71357]	0.016696 (0.02391) [0.69815]	-0.003029 (0.01068) [-0.28369]	0.847853 (0.02813) [30.1374]#
SA REIT Index(-2)	-4.86E-17 (0.02591) [-1.9e-15]	-7.36E-18 (0.02466) [-3.0e-16]	2.37E-17 (0.02401) [9.9e-16]	-3.19E-17 (0.02689) [-1.2e-15]	1.40E-16 (0.05197) [2.7e-15]	-8.53E-17 (0.07678) [-1.1e-15]	7.68E-18 (0.01814) [4.2e-16]	4.90E-17 (0.02536) [1.9e-15]	1.44E-17 (0.03520) [4.1e-16]	3.85E-18 (0.03131) [1.2e-16]	-1.58E-17 (0.01398) [-1.1e-15]	-2.39E-17 (0.03684) [-6.5e-16]
SA REIT Index(-3)	2.63E-17 (0.02591) [1.0e-15]	3.09E-17 (0.02466) [1.3e-15]	-1.87E-17 (0.02401) [-7.8e-16]	-1.59E-17 (0.02689) [-5.9e-16]	-5.35E-17 (0.05197) [-1.0e-15]	-1.42E-17 (0.07678) [-1.9e-16]	-6.51E-18 (0.01814) [-3.6e-16]	-1.90E-17 (0.02536) [-7.5e-16]	-1.77E-17 (0.03520) [-5.0e-16]	-5.76E-17 (0.03131) [-1.8e-15]	4.96E-18 (0.01398) [3.5e-16]	1.42E-16 (0.03684) [3.8e-15]
SA REIT Index(-4)	0.009099 (0.01972) [0.46132]	0.002463 (0.01877) [0.13120]	0.000388 (0.01828) [0.02121]	-0.008039 (0.02047) [-0.39273]	0.036687 (0.03956) [0.92728]	0.047144 (0.05845) [0.80663]	-0.007775 (0.01381) [-0.56304]	0.004835 (0.01931) [0.25040]	-0.009634 (0.02679) [-0.35958]	-0.003746 (0.02384) [-0.15716]	-0.002947 (0.01064) [-0.27685]	-0.165052 (0.02804) [-5.88623]#
$Adjusted\ R^2$	0.633038	0.646086	0.647019	0.648083	0.621795	0.608598	0.658639	0.631185	0.616630	0.639433	0.595015	0.659674
F-statistic	83.51610	88.32187	88.67934	89.08900	79.64140	75.37695	93.29203	82.86134	77.93732	85.82826	71.27803	93.71818
Akaike AIC	-5.818997	-5.917958	-5.971224	-5.744848	-4.426856	-3.646482	-6.532041	-5.861743	-5.206372	-5.440363	-7.052718	-5.115393
Schwarz SC	-5.696564	-5.795525	-5.848791	-5.622415	-4.304423	-3.524049	-6.409608	-5.739310	-5.083939	-5.317930	-6.930285	-4.992960

Note: In each cell, the first number is the coefficient, the number in rounded brackets is the standard error and the number in squared brackets is the t-test. In order for the t-statistic to be statistically significant for VAR values, the t-statistic should be at least 2 irrespective of being negative or positive, and # illustrates that the t-statistic is at least 2. The VAR results should read in conjunction with Cholesky decomposition as illustrated in fig. 3. SA stands for South Africa, U.S. for United States of America and UK for United Kingdom.

When interpreting the VAR results, one uses the t-statistic in square brackets in table 4.3 and the t-statistic should be at least 2 irrespective of the sign before the number. Figure 4.3 and table 4.3 indicate volatility spillovers that exist amongst the asset classes and markets, these spillovers are statistically significant which is illustrated by the # on some of the indices presented in table 4.3.

Broadly from figure 4.3 and table 4.3 for all indices, the shocks from one country emanate from the lagged (-1) shock in that country, with the t-statistic value ranging between around 20 and 40, the reactions are all positive. Reactions to shocks in one country and index originate from the fourth lagged shocks from the same country and index [i.e., U.S. equity (-4); U.S. equity], with all the reactions being negative and with values ranging between two and they are just under ten. The impact (value) of the fourth lag shock, compared to the first lagged shock suggest a smaller impact of its own past shock or volatility. Furthermore, the volatility spillovers are negatively correlated, this is important for portfolio diversification and risk mitigation. The above results reveal that the volatility of one market is strongly and significantly dependent on its own past volatility shocks. Kola (2021) found similar findings and/or revelations on their transatlantic study.

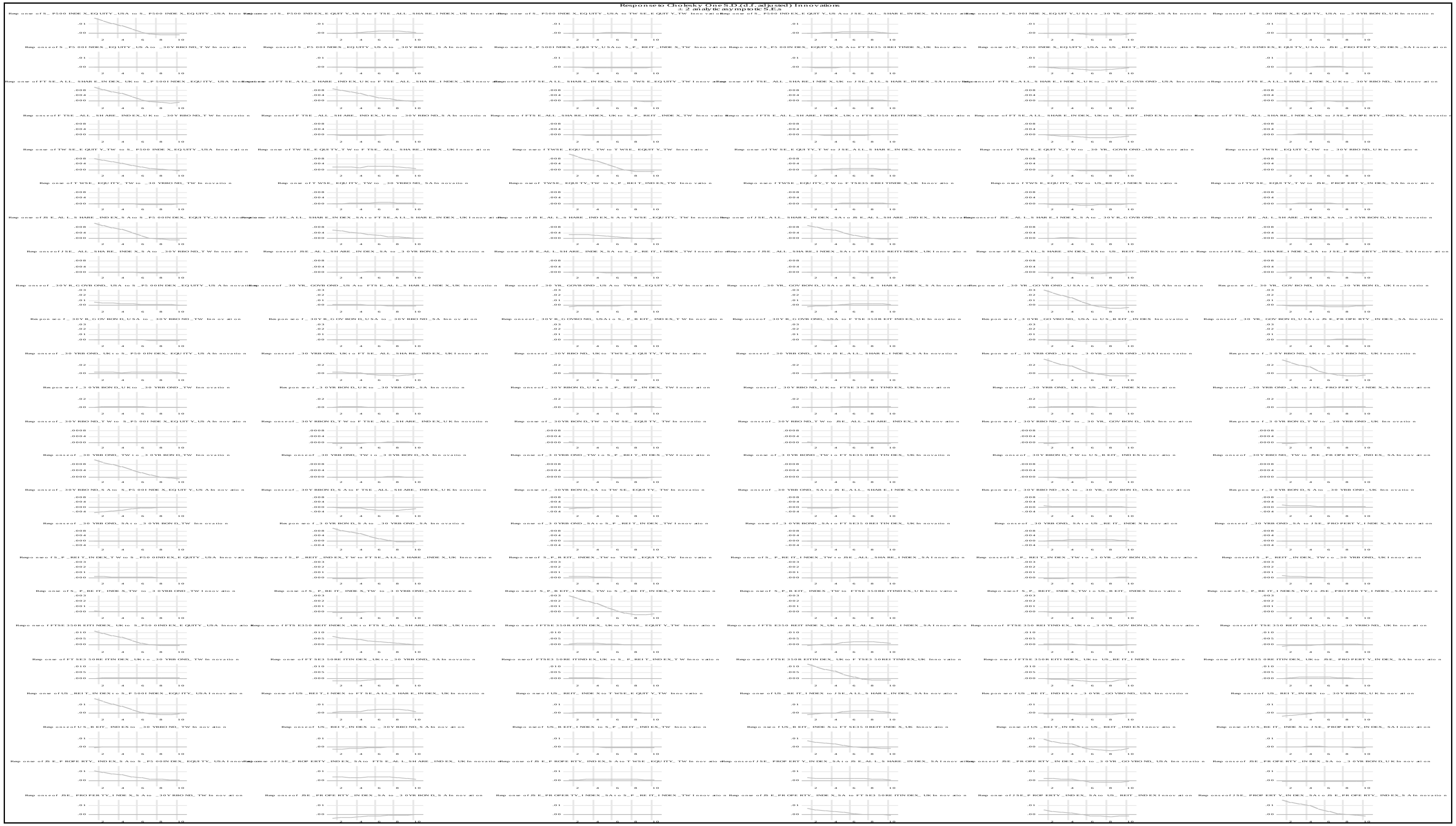
The U.S. and UK bond indices react to fourth lagged shocks from the U.S. equity index positively, this might be due to the increasing integration of listed property and bonds into capital markets (Zwane, 2021). It is also worth noting that as of the fourth quarter of 2021, the U.S. equity market holds 42% of the global equity market. This means that the movements in this index impacts other equity markets and markets that are correlated to the U.S. equity market. The fourth lag shock of the UK equity index causes negative shocks to U.S., UK and South African bond indices. The globalization of financial markets and the rise of foreign investors and eased restrictions of cross-border capital flow (Vo and Ellis, 2018) has led to a rise of the impact advanced economies have on emerging economies (i.e., UK equity index impact on South African bond index) the observed results are a common trend. In each cell, the second ratio in rounded brackets, illustrates the standard error term. According to Merkle (2018), a positive standard error term implies that there is information asymmetry in the time series. And Zwane (2024) suggested that there is herding behaviour during the study period. Based on Merkle (2018), information asymmetry creates an environment suitable for herding behaviour among investors.

The adjusted R^2 values are within the range of 0 to 1. They all are around the 60% mark indicating that movements of the indices are explained by movements of the significant indices. However, adjusted R^2 values are not very close to 1 which confirms the GARCH results which opined the availability of information asymmetry.

The main revelation is that indices, irrespective of their capital market product focus, react to first and fourth shocks emanating within and/or in between indices of different countries. This is probably to confirm that black swans have immediate and long-term effects on global markets, similar to the 2007/2009 subprime crisis. The diagnostic measures (Akaike and Schwarz) illustrate that the time series are skewed, partly, due to the presence of information asymmetry.

4.5.2.2 In-Sample

Figure 4. 4: In-sample Cholesky Decomposition



Note: The Cholesky decomposition is read in conjunction with the VAR(1,4) results in table 4.4.

Table 4. 4: In-Sample (1,4)

Parameters	U.S. Equity Index	UK Equity Index	Taiwan Equity Index	SA Equity Index	U.S. 30yr Bond	UK 30yr Bond	Taiwan 30yr Bond	SA 30yr Bond	U.S. REIT Index	UK REIT Index	Taiwan REIT Index	SA REIT Index
U.S. Equity Index(-1)	0.834509 (0.06821) [12.2338]#	0.015326 (0.06089) [0.25170]	0.019816 (0.05746) [0.34483]	0.023339 (0.06700) [0.34833]	-0.008350 (0.13337) [-0.06261]	-0.037772 (0.21245) [-0.17780]	0.001449 (0.00449) [0.32295]	-0.014605 (0.04975) [-0.29358]	0.000201 (0.09571) [0.00210]	0.030106 (0.07597) [0.39626]	0.006338 (0.01258) [0.50381]	0.013147 (0.09503) [0.13835]
U.S. Equity Index(-2)	-6.66E-18 (0.08921) [-7.5e-17]	2.49E-16 (0.07963) [3.1e-15]	1.49E-16 (0.07515) [2.0e-15]	-7.54E-17 (0.08763) [-8.6e-16]	-1.25E-16 (0.17442) [-7.2e-16]	3.20E-16 (0.27784) [1.2e-15]	6.98E-19 (0.00587) [1.2e-16]	-3.94E-17 (0.06506) [-6.1e-16]	7.73E-17 (0.12517) [6.2e-16]	-3.00E-16 (0.09936) [-3.0e-15]	1.97E-18 (0.01645) [1.2e-16]	-4.90E-16 (0.12428) [-3.9e-15]
U.S. Equity Index(-3)	-1.17E-16 (0.08921) [-1.3e-15]	-2.14E-16 (0.07963) [-2.7e-15]	-9.20E-17 (0.07515) [-1.2e-15]	1.50E-16 (0.08763) [1.7e-15]	-2.62E-16 (0.17442) [-1.5e-15]	-4.57E-16 (0.27784) [-1.6e-15]	8.99E-18 (0.00587) [1.5e-15]	8.82E-17 (0.06506) [1.4e-15]	-1.24E-16 (0.12517) [-9.9e-16]	1.32E-16 (0.09936) [1.3e-15]	2.05E-17 (0.01645) [1.2e-15]	3.25E-16 (0.12428) [2.6e-15]
U.S. Equity Index(-4)	-0.174876 (0.06812) [-2.56705]#	0.020728 (0.06081) [0.34088]	-0.039542 (0.05739) [-0.68903]	-0.022958 (0.06692) [-0.34309]	0.200491 (0.13319) [1.50530]	0.366105 (0.21217) [1.72557]	-0.001360 (0.00448) [-0.30335]	0.054485 (0.04968) [1.09665]	-0.055789 (0.09558) [-0.58369]	0.031633 (0.07587) [0.41691]	0.004781 (0.01256) [0.38055]	-0.037876 (0.09491) [-0.39910]
UK Equity Index(-1)	-0.007241 (0.06816) [-0.10623]	0.829191 (0.06084) [13.6289]#	0.007476 (0.05742) [0.13019]	-0.014057 (0.06695) [-0.20995]	0.022024 (0.13326) [0.16526]	0.006234 (0.21228) [0.02936]	0.000352 (0.00448) [0.07850]	-0.024604 (0.04971) [-0.49495]	-0.008343 (0.09563) [-0.08724]	-0.008047 (0.07592) [-0.10600]	-0.004496 (0.01257) [-0.35770]	0.020241 (0.09496) [0.21315]
UK Equity Index(-2)	2.12E-16 (0.08950) [2.4e-15]	-1.55E-16 (0.07989) [-1.9e-15]	2.86E-17 (0.07540) [3.8e-16]	-4.08E-16 (0.08791) [-4.6e-15]	7.85E-18 (0.17498) [4.5e-17]	-8.57E-16 (0.27874) [-3.1e-15]	2.25E-18 (0.00589) [3.8e-16]	-3.11E-16 (0.06527) [-4.8e-15]	-5.49E-16 (0.12557) [-4.4e-15]	2.89E-17 (0.09968) [2.9e-16]	-2.65E-17 (0.01651) [-1.6e-15]	-7.93E-17 (0.12468) [-6.4e-16]
UK Equity Index(-3)	5.97E-17 (0.08950) [6.7e-16]	1.10E-16 (0.07989) [1.4e-15]	1.75E-17 (0.07540) [2.3e-16]	5.87E-18 (0.08791) [6.7e-17]	4.52E-16 (0.17498) [2.6e-15]	5.74E-16 (0.27874) [2.1e-15]	-5.83E-18 (0.00589) [-9.9e-16]	2.66E-16 (0.06527) [4.1e-15]	6.13E-16 (0.12557) [4.9e-15]	4.20E-18 (0.09968) [4.2e-17]	-7.06E-18 (0.01651) [-4.3e-16]	7.28E-16 (0.12468) [5.8e-15]
UK Equity Index(-4)	0.052285 (0.06849) [0.76335]	-0.133181 (0.06114) [-2.17833]#	0.078602 (0.05770) [1.36221]	0.044419 (0.06728) [0.66021]	-0.198008 (0.13392) [-1.47860]	-0.371716 (0.21332) [-1.74251]	0.002946 (0.00451) [0.65361]	-0.110784 (0.04995) [-2.21773]#	0.139683 (0.09610) [1.45348]	0.004272 (0.07629) [0.05600]	-0.003333 (0.01263) [-0.26384]	0.072587 (0.09542) [0.76069]
Taiwan Equity Index(-1)	0.019620 (0.04727) [0.41506]	0.029700 (0.04219) [0.70390]	0.829586 (0.03982) [20.8327]#	0.026950 (0.04643) [0.58041]	-0.009970 (0.09242) [-0.10787]	-0.026868 (0.14722) [-0.18250]	-0.000469 (0.00311) [-0.15071]	0.013149 (0.03447) [0.38142]	0.016900 (0.06632) [0.25481]	0.024309 (0.05265) [0.46172]	0.001187 (0.00872) [0.13619]	0.020440 (0.06585) [0.31039]
Taiwan Equity Index(-2)	1.38E-17 (0.06150) [2.2e-16]	1.34E-17 (0.05490) [2.4e-16]	1.22E-16 (0.05181) [2.3e-15]	-6.80E-17 (0.06041) [-1.1e-15]	-6.49E-18 (0.12024) [-5.4e-17]	6.48E-17 (0.19154) [3.4e-16]	-9.47E-19 (0.00405) [-2.3e-16]	-2.92E-17 (0.04485) [-6.5e-16]	-8.12E-17 (0.08629) [-9.4e-16]	-4.29E-17 (0.06850) [-6.3e-16]	-4.05E-18 (0.01134) [-3.6e-16]	-8.02E-17 (0.08568) [-9.4e-16]
Taiwan Equity Index(-3)	2.48E-17 (0.06150) [4.0e-16]	-3.88E-17 (0.05490) [-7.1e-16]	-6.80E-17 (0.05181) [-1.3e-15]	-5.05E-17 (0.06041) [-8.4e-16]	1.06E-16 (0.12024) [8.8e-16]	1.42E-17 (0.19154) [7.4e-17]	1.33E-18 (0.00405) [3.3e-16]	-4.05E-17 (0.04485) [-9.0e-16]	-7.94E-17 (0.08629) [-9.2e-16]	9.71E-17 (0.06850) [1.4e-15]	3.95E-18 (0.01134) [3.5e-16]	7.07E-17 (0.08568) [8.2e-16]
Taiwan Equity Index(-4)	-0.009408 (0.04714) [-0.19958]	-0.028469 (0.04208) [-0.67659]	-0.175118 (0.03971) [-4.40976] #	-0.008018 (0.04630) [-0.17317]	-0.056038 (0.09216) [-0.60803]	-0.176044 (0.14681) [-1.19911]	0.000690 (0.00310) [0.22249]	-0.010094 (0.03438) [-0.29360]	-0.038199 (0.06614) [-0.57755]	-0.058709 (0.05250) [-1.11820]	-0.004464 (0.00869) [-0.51349]	0.007641 (0.06567) [0.11635]
SA Equity Index(-1)	0.022810 (0.05560) [0.41029]	-0.003694 (0.04962) [-0.07444]	0.011603 (0.04683) [0.24775]	0.832808 (0.05461) [15.2501] #	0.059394 (0.10870) [0.54642]	0.058136 (0.17315) [0.33576]	-0.001260 (0.00366) [-0.34458]	0.011687 (0.04055) [0.28825]	0.038332 (0.07800) [0.49142]	0.006173 (0.06192) [0.09969]	-0.002679 (0.01025) [-0.26132]	0.012837 (0.07745) [0.16574]
SA Equity Index(-2)	-2.13E-16 (0.07290)	-3.37E-17 (0.06507)	-1.65E-16 (0.06141)	3.78E-16 (0.07160)	1.16E-16 (0.14252)	3.28E-16 (0.22703)	5.07E-19 (0.00480)	2.58E-16 (0.05316)	3.17E-16 (0.10228)	2.24E-16 (0.08119)	2.28E-17 (0.01344)	4.28E-16 (0.10155)

	[-2.9e-15]	[-5.2e-16]	[-2.7e-15]	[5.3e-15]	[8.1e-16]	[1.4e-15]	[1.1e-16]	[4.9e-15]	[3.1e-15]	[2.8e-15]	[1.7e-15]	[4.2e-15]
SA Equity Index(-3)	9.43E-17	2.89E-17	6.27E-17	-1.84E-17	-2.25E-16	8.48E-18	-5.00E-18	-2.40E-16	-2.71E-16	-1.48E-16	-1.17E-17	-6.39E-16
	(0.07290)	(0.06507)	(0.06141)	(0.07160)	(0.14252)	(0.22703)	(0.00480)	(0.05316)	(0.10228)	(0.08119)	(0.01344)	(0.10155)
	[1.3e-15]	[4.4e-16]	[1.0e-15]	[-2.6e-16]	[-1.6e-15]	[3.7e-17]	[-1.0e-15]	[-4.5e-15]	[-2.6e-15]	[-1.8e-15]	[-8.7e-16]	[-6.3e-15]
SA Equity Index(-4)	0.047014	0.024087	0.032191	-0.126830	0.113285	0.080454	-0.000626	-0.001850	0.082938	0.082896	0.001645	0.073439
	(0.05541)	(0.04946)	(0.04668)	(0.05443)	(0.10834)	(0.17259)	(0.00365)	(0.04041)	(0.07775)	(0.06172)	(0.01022)	(0.07720)
	[0.84840]	[0.48697]	[0.68956]	[-2.33003]#	[1.04562]	[0.46617]	[-0.17176]	[-0.04577]	[1.06672]	[1.34309]	[0.16094]	[0.95128]
U.S. 30yr Bond(-1)	-0.003064	0.005194	0.001500	0.010850	0.821865	0.016445	-0.000114	0.001872	-0.021819	-0.003858	0.000724	-0.003691
	(0.02406)	(0.02148)	(0.02027)	(0.02364)	(0.04705)	(0.07495)	(0.00158)	(0.01755)	(0.03376)	(0.02680)	(0.00444)	(0.03353)
	[-0.12733]	[0.24181]	[0.07402]	[0.45900]	[17.4682]#	[0.21942]	[-0.07228]	[0.10665]	[-0.64623]	[-0.14393]	[0.16317]	[-0.11008]
U.S. 30yr Bond(-2)	-4.03E-17	3.84E-17	2.74E-17	-2.99E-18	-1.29E-16	1.27E-16	2.73E-18	2.44E-17	2.81E-17	3.99E-17	8.03E-19	-5.81E-17
	(0.03137)	(0.02800)	(0.02643)	(0.03082)	(0.06134)	(0.09770)	(0.00206)	(0.02288)	(0.04402)	(0.03494)	(0.00579)	(0.04370)
	[-1.3e-15]	[1.4e-15]	[1.0e-15]	[-9.7e-17]	[-2.1e-15]	[1.3e-15]	[1.3e-15]	[1.1e-15]	[6.4e-16]	[1.1e-15]	[1.4e-16]	[-1.3e-15]
U.S. 30yr Bond(-3)	3.09E-17	-1.44E-17	4.78E-18	1.13E-17	1.60E-16	-1.38E-16	-1.09E-18	2.44E-18	-3.50E-17	1.90E-17	3.43E-18	-1.92E-17
	(0.03137)	(0.02800)	(0.02643)	(0.03082)	(0.06134)	(0.09770)	(0.00206)	(0.02288)	(0.04402)	(0.03494)	(0.00579)	(0.04370)
	[9.9e-16]	[-5.1e-16]	[1.8e-16]	[3.7e-16]	[2.6e-15]	[-1.4e-15]	[-5.3e-16]	[1.1e-16]	[-7.9e-16]	[5.4e-16]	[5.9e-16]	[-4.4e-16]
U.S. 30yr Bond(-4)	-0.019292	-0.000517	-0.014579	-0.005246	-0.170882	0.032188	8.29E-05	0.004519	-0.050622	-0.022585	-0.000109	-0.018412
	(0.02407)	(0.02148)	(0.02028)	(0.02364)	(0.04706)	(0.07496)	(0.00158)	(0.01755)	(0.03377)	(0.02681)	(0.00444)	(0.03353)
	[-0.80155]	[-0.02408]	[-0.71902]	[-0.22190]	[-3.63135]#	[0.42940]	[0.05237]	[0.25746]	[-1.49904]	[-0.84249]	[-0.02463]	[-0.54911]
UK 30yr Bond(-1)	-0.003965	-0.005841	-0.006343	-0.007267	-0.016998	0.783671	0.000177	0.001945	0.006625	-0.003478	-0.001052	-0.008577
	(0.01536)	(0.01371)	(0.01294)	(0.01509)	(0.03004)	(0.04785)	(0.00101)	(0.01120)	(0.02156)	(0.01711)	(0.00283)	(0.02140)
	[-0.25807]	[-0.42591]	[-0.49009]	[-0.48154]	[-0.56588]	[16.3778]#	[0.17559]	[0.17358]	[0.30734]	[-0.20322]	[-0.37146]	[-0.40073]
UK 30yr Bond(-2)	2.23E-17	-3.51E-17	-2.48E-17	5.11E-18	1.07E-16	-1.22E-16	-2.24E-18	-9.45E-18	-5.87E-18	1.17E-17	-4.05E-19	6.61E-17
	(0.02000)	(0.01785)	(0.01684)	(0.01964)	(0.03909)	(0.06227)	(0.00132)	(0.01458)	(0.02805)	(0.02227)	(0.00369)	(0.02786)
	[1.1e-15]	[-2.0e-15]	[-1.5e-15]	[2.6e-16]	[2.7e-15]	[-2.0e-15]	[-1.7e-15]	[-6.5e-16]	[-2.1e-16]	[5.2e-16]	[-1.1e-16]	[2.4e-15]
UK 30y Bond(-3)	-6.19E-18	7.74E-18	-3.92E-18	-2.29E-17	-1.16E-16	1.21E-16	-6.62E-20	-2.06E-17	1.39E-17	-3.06E-17	-2.76E-18	-2.91E-17
	(0.02000)	(0.01785)	(0.01684)	(0.01964)	(0.03909)	(0.06227)	(0.00132)	(0.01458)	(0.02805)	(0.02227)	(0.00369)	(0.02786)
	[-3.1e-16]	[4.3e-16]	[-2.3e-16]	[-1.2e-15]	[-3.0e-15]	[1.9e-15]	[-5.0e-17]	[-1.4e-15]	[4.9e-16]	[-1.4e-15]	[-7.5e-16]	[-1.0e-15]
UK 30yr Bond(-4)	-0.011785	-0.005836	0.000634	-0.002067	-0.028407	-0.218629	0.000267	0.008448	-0.000427	-4.05E-05	-0.000652	-0.014975
	(0.01541)	(0.01375)	(0.01298)	(0.01513)	(0.03012)	(0.04799)	(0.00101)	(0.01124)	(0.02162)	(0.01716)	(0.00284)	(0.02146)
	[-0.76491]	[-0.42436]	[0.04884]	[-0.13660]	[-0.94303]	[-4.55620]#	[0.26341]	[0.75185]	[-0.01974]	[-0.00236]	[-0.22941]	[-0.69766]
Taiwan 30yr Bond(-1)	0.050590	0.044780	-0.035229	-0.037743	0.202334	0.411066	0.863676	0.024840	-0.000799	0.093021	-0.003569	0.079636
	(0.46114)	(0.41162)	(0.38848)	(0.45297)	(0.90159)	(1.43620)	(0.03034)	(0.33632)	(0.64701)	(0.51361)	(0.08504)	(0.64244)
	[0.10971]	[0.10879]	[-0.09068]	[-0.08332]	[0.22442]	[0.28622]	[28.4664]#	[0.07386]	[-0.00124]	[0.18111]	[-0.04197]	[0.12396]
Taiwan 30yr Bond(-2)	1.42E-16	-9.75E-17	-2.33E-17	-2.10E-16	1.92E-17	-4.21E-16	3.19E-17	-2.10E-16	-1.96E-16	-1.54E-16	-1.18E-17	-4.19E-17
	(0.61212)	(0.54639)	(0.51567)	(0.60128)	(1.19678)	(1.90641)	(0.04027)	(0.44643)	(0.85885)	(0.68177)	(0.11289)	(0.85277)
	[2.3e-16]	[-1.8e-16]	[-4.5e-17]	[-3.5e-16]	[1.6e-17]	[-2.2e-16]	[7.9e-16]	[-4.7e-16]	[-2.3e-16]	[-2.3e-16]	[-1.0e-16]	[-4.9e-17]
Taiwan 30yr Bond(-3)	-1.40E-17	3.79E-17	-7.79E-17	1.79E-16	1.54E-16	2.93E-16	1.20E-17	2.10E-16	3.01E-16	4.69E-18	-7.71E-18	2.95E-16
	(0.61212)	(0.54639)	(0.51567)	(0.60128)	(1.19678)	(1.90641)	(0.04027)	(0.44643)	(0.85885)	(0.68177)	(0.11289)	(0.85277)
	[-2.3e-17]	[6.9e-17]	[-1.5e-16]	[3.0e-16]	[1.3e-16]	[1.5e-16]	[3.0e-16]	[4.7e-16]	[3.5e-16]	[6.9e-18]	[-6.8e-17]	[3.5e-16]
Taiwan 30yr Bond(-4)	-0.036066	-0.072066	-0.114770	-0.123793	-0.377718	-0.392551	-0.133842	-0.082841	-0.054514	0.101638	0.005636	0.012213
	(0.46135)	(0.41180)	(0.38865)	(0.45317)	(0.90200)	(1.43684)	(0.03035)	(0.33647)	(0.64730)	(0.51384)	(0.08508)	(0.64272)

	[-0.07818]	[-0.17500]	[-0.29530]	[-0.27317]	[-0.41876]	[-0.27321]	[-4.40943]#	[-0.24621]	[-0.08422]	[0.19780]	[0.06624]	[0.01900]
SA 30yr Bond(-1)	-0.003966	-0.025054	0.019545	0.002236	-0.009775	0.005991	0.000468	0.830790	-0.008885	-0.037443	-0.000349	-0.008766
	(0.04807)	(0.04291)	(0.04050)	(0.04722)	(0.09399)	(0.14972)	(0.00316)	(0.03506)	(0.06745)	(0.05354)	(0.00887)	(0.06697)
	[-0.08250]	[-0.58385]	[0.48262]	[0.04735]	[-0.10400]	[0.04001]	[0.14807]	[23.6958]#	[-0.13173]	[-0.69930]	[-0.03941]	[-0.13089]
SA 30yr Bond(-2)	2.37E-17	-4.05E-17	4.32E-18	-7.15E-17	6.11E-17	1.86E-16	1.84E-18	-1.96E-17	2.14E-16	-1.56E-18	-2.78E-18	-5.70E-17
	(0.06294)	(0.05618)	(0.05302)	(0.06182)	(0.12305)	(0.19601)	(0.00414)	(0.04590)	(0.08830)	(0.07010)	(0.01161)	(0.08768)
	[3.8e-16]	[-7.2e-16]	[8.1e-17]	[-1.2e-15]	[5.0e-16]	[9.5e-16]	[4.4e-16]	[-4.3e-16]	[2.4e-15]	[-2.2e-17]	[-2.4e-16]	[-6.5e-16]
SA 30yr Bond(-3)	-5.12E-17	-1.22E-17	4.96E-17	9.53E-17	-1.33E-16	1.77E-16	-9.28E-19	-1.80E-17	-1.10E-16	4.91E-18	-2.46E-18	-1.59E-17
	(0.06294)	(0.05618)	(0.05302)	(0.06182)	(0.12305)	(0.19601)	(0.00414)	(0.04590)	(0.08830)	(0.07010)	(0.01161)	(0.08768)
	[-8.1e-16]	[-2.2e-16]	[9.4e-16]	[1.5e-15]	[-1.1e-15]	[9.0e-16]	[-2.2e-16]	[-3.9e-16]	[-1.2e-15]	[7.0e-17]	[-2.1e-16]	[-1.8e-16]
SA 30yr Bond(-4)	-0.004104	0.010758	0.033434	0.026164	-0.016017	-0.057035	0.001427	-0.154790	-0.006466	-0.014025	0.001922	-0.055323
	(0.04797)	(0.04281)	(0.04041)	(0.04712)	(0.09378)	(0.14939)	(0.00316)	(0.03498)	(0.06730)	(0.05342)	(0.00885)	(0.06682)
	[-0.08556]	[0.25126]	[0.82740]	[0.55531]	[-0.17079]	[-0.38179]	[0.45225]	[-4.42483]#	[-0.09608]	[-0.26253]	[0.21726]	[-0.82790]
U.S. REIT Index(-1)	-0.084456	-0.058356	-0.046272	-0.042691	-0.058392	0.060317	-0.001255	0.049653	0.705936	-0.083263	-0.006009	-0.086425
	(0.05174)	(0.04619)	(0.04359)	(0.05083)	(0.10117)	(0.16115)	(0.00340)	(0.03774)	(0.07260)	(0.05763)	(0.00954)	(0.07209)
	[-1.63217]	[-1.26345]	[-1.06150]	[-0.83992]	[-0.57718]	[0.37428]	[-0.36862]	[1.31574]	[9.72354]#	[-1.44474]	[-0.62975]	[-1.19891]
U.S. REIT Index(-2)	-8.01E-18	-2.20E-16	-9.56E-17	9.36E-17	2.52E-16	-5.07E-17	-8.25E-19	2.04E-17	9.63E-17	3.35E-16	4.73E-18	3.77E-16
	(0.06781)	(0.06053)	(0.05713)	(0.06661)	(0.13258)	(0.21119)	(0.00446)	(0.04946)	(0.09514)	(0.07553)	(0.01251)	(0.09447)
	[-1.2e-16]	[-3.6e-15]	[-1.7e-15]	[1.4e-15]	[1.9e-15]	[-2.4e-16]	[-1.9e-16]	[4.1e-16]	[1.0e-15]	[4.4e-15]	[3.8e-16]	[4.0e-15]
U.S. REIT Index(-3)	5.10E-17	1.47E-16	4.95E-18	-1.41E-16	8.62E-17	3.49E-16	-6.00E-18	-1.84E-16	5.18E-18	-2.36E-16	-1.77E-17	-2.94E-16
	(0.06781)	(0.06053)	(0.05713)	(0.06661)	(0.13258)	(0.21119)	(0.00446)	(0.04946)	(0.09514)	(0.07553)	(0.01251)	(0.09447)
	[7.5e-16]	[2.4e-15]	[8.7e-17]	[-2.1e-15]	[6.5e-16]	[1.7e-15]	[-1.3e-15]	[-3.7e-15]	[5.4e-17]	[-3.1e-15]	[-1.4e-15]	[-3.1e-15]
U.S. REIT Index(-4)	-0.091328	-0.084011	-0.004335	-0.011496	-0.131117	-0.057814	0.000799	0.014607	-0.284735	-0.098001	-0.002840	-0.058340
	(0.05177)	(0.04621)	(0.04361)	(0.05085)	(0.10122)	(0.16124)	(0.00341)	(0.03776)	(0.07264)	(0.05766)	(0.00955)	(0.07212)
	[-1.76408]	[-1.81798]	[-0.09940]	[-0.22607]	[-1.29538]	[-0.35857]	[0.23445]	[0.38687]	[-3.91992] #	[-1.69958]	[-0.29750]	[-0.80888]
UK REIT Index(-1)	0.039947	0.011818	0.023675	0.017861	0.012338	-0.027259	0.001215	-0.038955	0.041734	0.842907	0.003827	0.038348
	(0.05277)	(0.04710)	(0.04445)	(0.05183)	(0.10317)	(0.16434)	(0.00347)	(0.03848)	(0.07404)	(0.05877)	(0.00973)	(0.07351)
	[0.75702]	[0.25090]	[0.53258]	[0.34458]	[0.11959]	[-0.16587]	[0.35005]	[-1.01222]	[0.56368]	[14.3417] #	[0.39328]	[0.52164]
UK REIT Index(-2)	-5.45E-17	2.08E-16	-2.78E-17	1.14E-16	-3.22E-16	2.49E-16	-1.95E-18	9.57E-17	-9.14E-18	-2.86E-16	2.02E-18	-1.68E-16
	(0.06887)	(0.06147)	(0.05802)	(0.06765)	(0.13465)	(0.21448)	(0.00453)	(0.05023)	(0.09663)	(0.07670)	(0.01270)	(0.09594)
	[-7.9e-16]	[3.4e-15]	[-4.8e-16]	[1.7e-15]	[-2.4e-15]	[1.2e-15]	[-4.3e-16]	[1.9e-15]	[-9.5e-17]	[-3.7e-15]	[1.6e-16]	[-1.8e-15]
UK REIT Index(-3)	-9.76E-18	-5.25E-17	4.84E-17	9.83E-17	-1.56E-16	-4.21E-16	5.36E-18	1.06E-16	1.96E-17	1.90E-16	1.09E-17	-1.10E-16
	(0.06887)	(0.06147)	(0.05802)	(0.06765)	(0.13465)	(0.21448)	(0.00453)	(0.05023)	(0.09663)	(0.07670)	(0.01270)	(0.09594)
	[-1.4e-16]	[-8.5e-16]	[8.3e-16]	[1.5e-15]	[-1.2e-15]	[-2.0e-15]	[1.2e-15]	[2.1e-15]	[2.0e-16]	[2.5e-15]	[8.6e-16]	[-1.1e-15]
UK REIT Index(-4)	0.066076	0.055206	0.030195	0.000551	0.109033	0.047178	-0.001094	-0.022680	0.088529	-0.102960	0.002891	0.045719
	(0.05271)	(0.04705)	(0.04440)	(0.05177)	(0.10305)	(0.16415)	(0.00347)	(0.03844)	(0.07395)	(0.05870)	(0.00972)	(0.07343)
	[1.25364]	[1.17342]	[0.68004]	[0.01064]	[1.05807]	[0.28741]	[-0.31553]	[-0.59002]	[1.19713]	[-1.75388]	[0.29745]	[0.62263]
Taiwan REIT Index(-1)	-0.012871	-0.042586	-0.005550	-0.039319	0.003621	-0.076669	-0.001134	-0.009068	-0.053873	-0.025724	0.815085	-0.001487
	(0.16545)	(0.14768)	(0.13938)	(0.16252)	(0.32347)	(0.51528)	(0.01089)	(0.12066)	(0.23214)	(0.18427)	(0.03051)	(0.23049)
	[-0.07780]	[-0.28836]	[-0.03982]	[-0.24194]	[0.01119]	[-0.14879]	[-0.10420]	[-0.07515]	[-0.23207]	[-0.13960]	[26.7139]#	[-0.00645]
Taiwan REIT Index(-2)	1.62E-17	-1.02E-16	6.10E-18	-1.60E-16	-3.59E-17	1.01E-16	2.77E-18	-6.35E-17	-2.25E-16	6.46E-17	-2.43E-17	1.42E-16
	(0.21506)	(0.19197)	(0.18118)	(0.21125)	(0.42048)	(0.66980)	(0.01415)	(0.15685)	(0.30175)	(0.23953)	(0.03966)	(0.29961)

	[7.5e-17]	[-5.3e-16]	[3.4e-17]	[-7.6e-16]	[-8.5e-17]	[1.5e-16]	[2.0e-16]	[-4.1e-16]	[-7.4e-16]	[2.7e-16]	[-6.1e-16]	[4.8e-16]
Taiwan REIT Index(-3)	-5.73E-17 (0.21506) [-2.7e-16]	-5.82E-17 (0.19197) [-3.0e-16]	3.62E-17 (0.18118) [2.0e-16]	-3.73E-17 (0.21125) [-1.8e-16]	9.43E-17 (0.42048) [2.2e-16]	-1.18E-16 (0.66980) [-1.8e-16]	3.23E-18 (0.01415) [2.3e-16]	1.05E-16 (0.15685) [6.7e-16]	1.84E-16 (0.30175) [6.1e-16]	-4.04E-17 (0.23953) [-1.7e-16]	8.85E-18 (0.03966) [2.2e-16]	-5.10E-17 (0.29961) [-1.7e-16]
Taiwan REIT Index(-4)	-0.048171 (0.16548) [-0.29110]	-0.065955 (0.14771) [-0.44653]	0.014598 (0.13940) [0.10472]	-0.093520 (0.16255) [-0.57534]	0.049841 (0.32353) [0.15405]	0.050041 (0.51537) [0.09710]	-0.002542 (0.01089) [-0.23347]	-0.005561 (0.12069) [-0.04608]	-0.129945 (0.23218) [-0.55968]	-0.056243 (0.18431) [-0.30516]	-0.183697 (0.03052) [-6.01950]#	-0.069621 (0.23053) [-0.30200]
SA REIT Index(-1)	0.020338 (0.03044) [0.66814]	0.023897 (0.02717) [0.87951]	0.016782 (0.02564) [0.65444]	0.021002 (0.02990) [0.70238]	-0.002118 (0.05951) [-0.03559]	-0.035027 (0.09480) [-0.36947]	0.000390 (0.00200) [0.19459]	-0.010265 (0.02220) [-0.46236]	0.029869 (0.04271) [0.69935]	0.028814 (0.03390) [0.84987]	0.001515 (0.00561) [0.26994]	0.858466 (0.04241) [20.2434]#
SA REIT Index(-2)	5.47E-17 (0.03994) [1.4e-15]	-6.16E-17 (0.03565) [-1.7e-15]	3.92E-17 (0.03365) [1.2e-15]	-8.51E-17 (0.03923) [-2.2e-15]	1.02E-16 (0.07809) [1.3e-15]	-9.55E-17 (0.12440) [-7.7e-16]	9.97E-20 (0.00263) [3.8e-17]	-2.78E-17 (0.02913) [-9.5e-16]	8.28E-17 (0.05604) [1.5e-15]	-7.13E-17 (0.04449) [-1.6e-15]	-4.47E-18 (0.00737) [-6.1e-16]	-7.42E-17 (0.05564) [-1.3e-15]
SA REIT Index(-3)	-8.13E-17 (0.03994) [-2.0e-15]	8.53E-18 (0.03565) [2.4e-16]	1.98E-18 (0.03365) [5.9e-17]	3.31E-17 (0.03923) [8.4e-16]	-6.42E-17 (0.07809) [-8.2e-16]	1.24E-16 (0.12440) [1.0e-15]	1.41E-18 (0.00263) [5.4e-16]	5.07E-17 (0.02913) [1.7e-15]	-1.30E-16 (0.05604) [-2.3e-15]	6.60E-17 (0.04449) [1.5e-15]	2.60E-18 (0.00737) [3.5e-16]	1.07E-16 (0.05564) [1.9e-15]
SA REIT Index(-4)	0.004960 (0.03024) [0.16400]	-0.006995 (0.02699) [-0.25912]	-0.010209 (0.02548) [-0.40075]	-0.016705 (0.02971) [-0.56235]	0.035913 (0.05913) [0.60740]	0.050881 (0.09418) [0.54024]	4.22E-05 (0.00199) [0.02121]	0.013469 (0.02206) [0.61070]	-0.014050 (0.04243) [-0.33114]	-0.006474 (0.03368) [-0.19220]	0.001166 (0.00558) [0.20916]	-0.157708 (0.04213) [-3.74337]#
$Adjusted\ R^2$	0.631954	0.645918	0.652810	0.645786	0.609198	0.591686	0.653982	0.658023	0.604246	0.633191	0.598225	0.668271
F-statistic	41.27915	43.79287	45.10791	43.76820	37.56775	34.99344	45.33671	46.13786	36.81664	41.49404	35.92839	48.25693
Akaike AIC	-5.391159	-5.618371	-5.734093	-5.426917	-4.050244	-3.119066	-10.83363	-6.022467	-4.713838	-5.175631	-8.772267	-4.728041
Schwarz SC	-5.172580	-5.399792	-5.515514	-5.208339	-3.831666	-2.900487	-10.61505	-5.803888	-4.495259	-4.957052	-8.553688	-4.509462

Note: In each cell, the first number is the coefficient, the number in rounded brackets is the standard error and the number in squared brackets is the t-test. In order for the t-statistic to be statistically significant for VAR values, the t-statistic should be at least 2 irrespective of being negative or positive and illustrates that the t-statistic is at least 2. The VAR results should read in conjunction with Cholesky decomposition as illustrated in fig. 4. SA stands for South Africa, U.S. for United States of America and UK for United Kingdom.

Broadly from Figure 4.4 and Table 4.4 for all indices, present similar results to the out-of-sample modelling. The shocks from one country emanate from the lagged (-1) shock in that country, with a t-statistic value that is positive. Similar, to the out-of-sample results, reactions to shocks in one country and index originate from the fourth lagged shocks from the same country and index [i.e., U.S. equity (-4); U.S. equity], with all the reactions being negative and with values ranging between two and it is just under ten.

The U.S. and UK bond indices react to fourth lagged shocks from the U.S. equity index positive and this is brought on by the increased integration of bonds and listed property into capital markets (Zwane, 2021). The fourth lag shock of the UK equity index causes negative shocks to the South African bond index.

Similar, to the out-of-sample result, the adjusted R^2 values are all around 0.6, which suggests that movements of the indices are explained by movements of the significant indices; however, there is availability of information asymmetry as opined by the GARCH results. The similarity between the out-of-sample and the in-sample results, confirm the strength of the VAR(1,4) analysis. It can be inferred from Merkle (2018) that when out-of-sample and in-sample results are similar it verifies the strength and robustness of the two time series data.

The salient and rare revelation, both from the VAR(1,4) out-of-and in-samples is that some shocks (be one-lagged or four-lagged) are statistically significant with an absolute value of at least ten. On the policy and economic fronts, those findings confirm that intraday investors will definitely benefit from worldwide integrated global markets, comprising of the U.S., the UK, Taiwan and South Africa, in particular on the integration based on bonds, equities and listed real estate indices.

4.5.3 Robustness Test

The robustness is based on the Markov-regime switching model, and that analysis, follows hereafter.

Table 4. 5: Markov-Regime Switching Results

Out-of-Sample				
Panel G: Equities				
Regime	U.S.	UK	Taiwan	South Africa
1	-3.7490 (0.0000)***	-12.2505 (0.0000)***	-3.8534 (0.0000)***	-3.4201 (0.0000)***
2	-10.6979 (0.0000)***	-3.5155 (0.0000)***	-12.9541 (0.0000)***	-11.6574 (0.0000)***
Panel H: Bonds				
Regime	U.S.	UK	Taiwan	South Africa
1	-3.2113 (0.0000)***	-2.6812 (0.0000)***	-21.8537 (0.0000)***	-3.7914 (0.0000)***
2	-11.0341 (0.0000)***	-11.2481 (0.0000)***	-3.3161 (0.0000)***	-13.0541 (0.0000)***
Panel I: Listed Real Estate				
Regime	U.S.	UK	Taiwan	South Africa
1	-3.1353 (0.0000)***	-3.2698 (0.0000)***	-4.2164 (0.0000)***	-3.4137 (0.0000)***
2	-12.4001 (0.0000)***	-11.8279 (0.0000)***	-12.9687 (0.0000)***	-12.8502 (0.0000)***
In-Sample				
Panel J: Equities				
Regime	U.S.	UK	Taiwan	South Africa
1	0.0015 (0.2992)	0.0107 (0.0001)***	-0.0347 (0.0000)***	0.0433 (0.0244)**
2	0.005106 (0.0004)***	-0.0464 (0.0000)***	0.0142 (0.0000)***	-0.0232 (0.2076)
Panel K: Bonds				
Regime	U.S.	UK	Taiwan	South Africa
1	-2.5704 (0.0000)***	-11.0181 (0.0000)***	-2.13-e05 (0.8716)	-3.6447 (0.0000)***
2	-10.7649 (0.0000)***	-2.0923 (0.0000)****	-0.0152 (0.0000)***	-12.3931 (0.0000)***
Panel L: Listed Real Estate				
Regime	U.S.	UK	Taiwan	South Africa
1	4.81e-05 (0.9775)	-3.1652 (0.0000)***	-19.2404 (0.0000)***	0.0920 (0.0000)***
2	0.0039 (0.0235)**	-12.7307 (0.0000)***	-4.9075 (0.0000)***	-0.0155 (0.0090)***

Note: The U.S. stands for the United States of America and the UK stands for the United Kingdom. Each cell, the first ratio is the coefficient, and the second bracketed ratio is the statistical significance, i.e. alpha, and***, **, * illustrate statistical significance at 1%, 5% and 10%; respectively.

From table 4.5, the out-of-sample results illustrate that both first and second regimes of the equities markets across the four countries are negative and about a third of the second regime results is higher than the first regimes throughout the presentations. Kola (2021) illustrated that the first regimes influence the second regimes, including the direction correlation of signs of both regimes. Thus, if first Markov regimes are positive (negative), then the second regimes will be positive (negative). The pattern of regimes for out-of-sample is the same throughout bonds and real estate indices. It can be inferred from Ilzetzki et al. (2013) that negative regimes reveal insightful shocks and high risk based off correlation among other features. Moreover, Mazibuko et al. (2021) suggest that the risk, especially of collapsing markets and the risk is higher when the size of the security and/or asset is big-the U.S. is the biggest market in the world. The UK is the biggest market in Europe and Taiwan is one of the biggest markets in Asia and South Africa is the biggest market in Africa. Therefore, the revelations of the out-of-sample time series are unsurprising.

The in-sample results reveal similar findings as the out-of-sample results, except for the in-sample time series, the first and second regimes do not necessarily have the same signs, throughout the in-sample results. That would probably imply short time series have cancelation effects on its regimes. Hence, the indicative regimes are from the out-of-sample time series.

Table 4. 6: Markov Transition-Constant Transition Probabilities

Panel M: Equities									
Sample	Regime	U.S.		UK		Taiwan		South Africa	
		1	2	1	2	1	2	1	2
Out-of-Sample	1	0.5033	0.4967	0.7498	0.2502	0.5008	0.4992	0.1748	0.8252
	2	0.3498	0.6503	0.7504	0.2497	0.3373	0.6627	0.2501	0.7499
In-Sample	1	0.1018	0.8982	0.4752	0.5248	0.0058	0.9942	0.0011	0.9989
	2	0.2515	0.7485	0.3288	0.6712	0.6671	0.3329	0.1823	0.8177
Panel N: Bonds									
Sample	Regime	U.S.		UK		Taiwan		South Africa	
		1	2	1	2	1	2	1	2
Out-of-Sample	1	0.5025	0.4976	0.4906	0.5094	0.9900	0.0099	0.5010	0.4989
	2	0.3316	0.6684	0.3312	0.6688	0.3467	0.6534	0.3356	0.6644
In-Sample	1	0.6657	0.3343	0.0266	0.9735	0.8286	0.1714	0.0046	0.9954
	2	0.5053	0.4947	0.2493	0.7507	0.4364	0.5636	0.2561	0.77439
Panel O: Listed Real Estate									
Sample	Regime	U.S.		UK		Taiwan		South Africa	
		1	2	1	2	1	2	1	2
Out-of-Sample	1	0.0053	0.9947	0.0239	0.9760	0.4997	0.5003	0.0036	0.9964
	2	0.2552	0.7448	0.2486	0.7514	0.1643	0.8357	0.5629	0.4371
In-Sample	1	0.0189	0.9811	0.4866	0.5134	0.9802	0.0198	0.6434	0.3566
	2	0.2563	0.7437	0.3275	0.6726	0.0076	0.9924	0.5018	0.4982

Note: The U.S. stands for the United States of America and the UK stands for the United Kingdom.

Table 4.6 shows the constant transition probabilities of the Markov-regime switching model; both for out-of and in-sample time series. On average, for both out-of and in-sample, the first and second probabilities, if the first regime occurs, then the first regimes have a higher chance and/or probability of transition. The latter finding is unsurprising, given that the first regime in this case, it is the lead regime. The same finding is mirrored for the second regime, when the second regime is the lead regime in terms of transition. The results are the same irrespective of the market product of the country of occurrence. Kola (2021) illustrated the same finding for the transatlantic organization.

Table 4. 7: Markov Transition-Constant Expected Durations

Panel P: Equities								
Sample	U.S.		UK		Taiwan		South Africa	
	1	2	1	2	1	2	1	2
Out-of-Sample	2.0133	2.8592	3.9961	1.3327	2.0032	2.9645	1.2118	3.9989
In-Sample	1.1133	3.9763	1.9055	3.0409	1.0058	1.4989	1.0011	5.4849
Panel Q: Bonds								
Sample	U.S.		UK		Taiwan		South Africa	
	1	2	1	2	1	2	1	2
Out-of-Sample	2.0099	3.0158	1.9633	3.0191	100.3506	2.8848	2.0042	2.9797
In-Sample	2.9909	1.9792	1.0273	4.0111	5.8329	2.2915	1.0046	3.9042
Panel R: Listed Real Estate								
Sample	U.S.		UK		Taiwan		South Africa	
	1	2	1	2	1	2	1	2
Out-of-Sample	1.0054	3.9186	1.0246	4.0221	1.9986	6.0859	1.0036	1.7766
In-Sample	1.0193	3.9019	1.9479	3.0539	50.6120	132.2246	2.8041	1.9929

Note: The U.S. stands for the United States of America and the UK stands for the United Kingdom.

Table 4.7 illustrate the duration of different regimes for the U.S., the UK, Taiwan and South Africa. Fundamentally, irrespective of the market, first regimes last longer than second regimes. This is interesting because in this study, the two major global superpowers-the U.S. and the UK, are included, while in Kola (2021), the focus is on major emerging markets across the globe. Similar to Kola (2021), this study finds that durations are shorter for real estate indices than other highly liquid products-bonds and equities. One potential future investigation is why real estate indices have shorter durations than bonds and equities indices, at least based on this study and Kola (2021).

4.6 Conclusion

As expected during herding, volatility is reactionary and persistent throughout the time series. Second, the VAR(1,4) results show that irrespective, whether it is one-lag all the way to the fourth-lag, there are reactive shocks across equities, bonds and real estate across the four countries. Interestingly, the statistical significance for VAR(1,4) has absolute values as high as twenty. Third, in terms of switching regimes, the first regimes tend to lead and give direction to subsequent occurring regimes.

The implications of this study are as follows. First, information asymmetry is an asset and in the context this study, asymmetrical information leads to herding behaviour. The asymmetrical information is desirable and profitable to intraday investors. Second, based on the VAR(1,4), it seems that there is value in integrating the U.S., the UK, Taiwan and South Africa. In order to minimise the integration of risk, the countries can start by integrating within the same product range and gradually move to in between different products. This is because the VAR(1,4) confirms findings of evidentiary value. Finally, investors and policy makers need to be aware of risks among and in between products when creating global market policies. Thus, appropriate policies should anchor global markets; however, those policies should not create unnecessary bureaucracy and risks in stock markets.

5 Real Estate Herding Behaviour

5.1 Introduction to Real Estate Herding Behaviour

Then, the question is whether those similarities and inter-governmental relations warrant newer indices? To the later question in the last paragraph, Zwane (2022) explored volatility risk among the same countries used in Zwane (2024) and exactly on the same indices. Zwane (2022) uses both univariate and multivariate time series analysis. The confirmation that volatility risk herd from the developed markets into the emerging markets in Zwane (2022) is startling at this point. Interestingly, the latter finding is consistent across all three indices-(i) bonds, (ii) equities and (iii) real estate. A novel finding from Zwane (2022) is that vector autoregressive (from here, VAR), when lagged to 4, confirms that newer indices of bonds, equities and real estate nature are feasible among the listed countries.

Given that the main illustration in Zwane (2022) is largely underpin by volatility risk, then, can a volatility measures be trusted? Whited and Wu (2006) studied financial constraints risk. Basically, the authors explored how external finances constraint the returns of stocks. Just like this study, Whited and Wu (2006) used an index-Kaplan and Zingales (1997) equity index. One of the key findings of Whited and Wu (2006) is that undiversifiable risk is persistent in financial markets. Note that undiversifiable risk is simply volatility or market risk. However, not explicitly stated in Whited and Wu (2006), it seems that market volatility risk is stochastic and hard to mitigate indeed.

With the advent of the dot-com bubble and the stock market crash, investors have been cautionary in where and how they choose to invest, which has led to the redirection of investment funds away from financial markets to the real estate market in the early 2000s (Lin and Li, 2019). The real estate market has incited a great deal of research interest due to the subprime crisis and the behaviour of investors that led to the crisis (Lin and Li, 2019). It has been found that institutional[1] herding is more prevalent in the bond market, especially with speculation-grade bonds (Cai et al, 2019). The price impact of institutional herding in the bond market has presented asymmetric findings on the sell herding and the buy herding (Cai et al, 2019). One aspect of investment behaviour that grows interest is herding behaviour in real estate, specifically in REITs. Herding is characterized by investors mimicking the actions (selling/buying) of others in a group for some time; these investors dismiss their own information in leu of investments based on the group (Philippas et al, 2013; Dewan and Dharn, 2019; Lin and Li, 2019; Aharon, 2021).

[1] Institutional means investments held by institutions such as asset managers and pension funds.

Herding affects market prices, attributes of risk and thus volatility and return models, ultimately driving fundamental value away (Lin and Li, 2019; Dewan and Dharn, 2019). The effects of herding impede the value discovery process of the market mechanism, which disrupts the asset pricing theory because investors do not have access to private information, which may lead to an augmented demand (Philippas et al., 2013; Dewan and Dharn, 2019). In times of market volatility, herding may jeopardize financial stability, and the first adverse market shocks may be intensified and augmented by pro-cyclical market mechanisms brought on by herding behaviour (Philippas et al., 2013). Herding behaviour has been identified as a risk amplifier (Cai et al, 2019) with a dynamic nature. Furthermore, herding behaviour has been shown to cause the divergence of asset returns away from their market value which in turn brings about volatility and renders markets inefficient (Yasir and Onder, 2023).

Herding has been shown to be more pronounced during precarious periods in the market which leads to investors abandoning their own information and following others to reduce their exposure to risk in times of uncertainty (Aharon, 2021). The assessment of herding behaviour under precarious, uncertain and fear sentiment is crucial for risk management purposes, hedging strategies and asset allocation, market stability and the price discovery mechanism (Aharon, 2021).

Although, the illustrations in Zwane (2021 and 2022) show systematic directional patterns, which can be linked to herding behaviour, the big question on whether there is herding or not, is not precisely confirmed in Zwane (2021 and 2022). This is the main investigation of this study. The prior scholarship close to this are Lakonishok et al. (1992), Christie and Huang (1995), and Change et al. (2000). The reason behind comparison of the three mentioned articles with this study is because those three articles came up with main herding models-(i) Lakonishok et al, (1992) model (from here, LSV), (ii) Cross-Sectional Absolute Deviation (CSAD, thereafter) (See; Chang et al. 2000) and (iii) Cross-Sectional Standard Deviatoon (CSSD) (See; Christie and Huang 1995). The three mentioned studies tested the three models on stock prices, while this study uses indexes. The laboratories are different-(i) Lakonishok et al. (1992), and Christie and Huang (1995) used the United States of America (U.S.), (ii) Chang et al. (2000) focused on U.S., Hong Kong, Japan, South Korea and Taiwan, while (iii) this study contrast emerged markets (i.e. the U.S. and the UK) and emerging markets (i.e. Taiwan and South Africa). Thus, this study explores herding among four continents (i.e., America, Europe, Far Asia and Africa) among its unique settings. Fundamentally, (i) Lakonishok et al. (1992) found herding among institutions destabilizes stock prices, (ii) Christie and Huang (1995) illustrated that herding is sensitive to down and up turns of stock markets, and (iii) Chang et al. (2000) exemplified that herding is consistent with directional asymmetry-this is consistent with the findings in Kola (2021).

The results of this study reveal the following. Herding usually moves from emerged markets into the emerging markets. Kumar et al. (2021) came to the same conclusion about directional movements when they used Asia-Pacific region as the laboratory. The CSSD model shows no herding at all, while the CSAD model confirms herding in the emerging markets. Finally, herding is more inherent in real estate indices than in individual REITs.

The balance of the paper proceeds as follows. Section 5.2 is on literature review. Section 5.3 is on modelling and Section 5.4 is on empirical application. Section 5.5 concludes this study.

5.2 Literature Review

Several frameworks have been used to investigate herding behaviour across various markets. These models include the traditional LSV, CSSD and CSAD models. The literature below seeks to explore the character, strengths and weaknesses of the three most popularly used models.

5.2.1 Asymmetric Herding

The LSV model is based on the tendency of investment managers ending up on the same side of the market in a given stock in a given quarter (Lakonishok et al, 1992). Lakonishok et al (1992) evaluated the impact of institutional trading on stock prices. The study used data of 769 funds made up predominantly of tax-exempt pension funds. The investigation analysed two positions on institutional trading which are said to destabilise prices: herding by institutional investors and positive feedback trading (Lakonishok et al, 1992). The outcome of the study showed that pension managers do not exhibit trading behaviour that destabilise prices (Lakonishok et al, 1992).

The sample data was collected from SEI which at the time held the opinion and definition that equity funds hold about 90% of their assets in equities (Lakonishok et al, 1992). Herding by these funds was measured by estimating the tendency of fund managers to end up on the same side of the market in a given stock in a given quarter; thereby, testing whether an inordinate number of fund managers buy or sell a stock (Lakonishok et al, 1992). The measure assumes that there is no herding at the individual stock level when in a given quarter half the fund managers increase their holdings in a given stock and half decrease their holdings (Lakonishok et al, 1992).

The measure purport that the herding by the fund managers of the 769 pension funds is relatively small in their trades in large stocks (Lakonishok et al, 1992). Herding was found in the smaller stocks however the herding is insignificant. The trading strategies of the pension fund managers do not follow negative or positive feedback strategies, with a weak correlation between price changes excess demand by fund managers (Lakonishok et al, 1992).

Herding has been flagged as a significant risk amplifier in the corporate bond market (Cai et al, 2019). It has been found that institutional herding is more prevalent in the bond market, especially with speculation-grade bonds (Cai et al, 2019). The price impact of institutional herding in the bond market has presented asymmetric findings on the sell herding and the buy herding stocks. The authors sought to determine if institutional investors herd in fixed-income markets and whether herding in the bond market destabilises bond prices. The study was conducted using various tools to reach its objectives. The LSV method was first used to approximate the magnitude of institutional herding, and then panel regression was used to assess the determinants of herding and how the herding differs with varying bond attributes and their past performance. Lastly, the price impact was evaluated by applying a portfolio approach which helped shed light on the provenance of herding in this situation (Cai et al, 2019).

The study assessed three types of institutional investors: mutual funds, insurance companies and pension funds. The secondary data for the study was collected from multiple resources; data on institutional investors that hold corporate bonds was sourced from Thomson Reuters Lipper eMAXX. The data holds quarter-end security-level corporate bond holdings of three classes: insurance companies, mutual funds, and pension funds. Data was also collected from the Fixed Investment Securities Database for additional bond and issuer information (Cai et al, 2019). The bond pricing data was collected from the Bank of America Merrill Lynch's (ML)4 Corporate Bond Index Database, which contains daily closing bid prices and is an excellent representative pool of U.S. public and corporate bonds. The data covered a period from the third quarter of 1998 to the third quarter of 2014.

Cai et al. (2019) found that herding occurs more in corporate bonds compared to equities, more notably with bonds with lower credit ratings. Insurance companies have a higher propensity to herd compared to pension and mutual funds, with sell herding being more vehement than buy herding process. Critical drivers of institutional herding in the bond market include rating changes, past bond performance and bond liquidity. The nonlinear herding-to-performance results presented by the authors found that bonds that have performed poorly in the past correlate with inordinately large sell herding. Furthermore, Cai et al. (2019) found a significant imitation-driven intertemporal herding in bonds. Due to its disruptive impact, sell herding may be a substantial risk to financial stability. Sell herding causes significant price distortions due to its short-term price effects, which in turn leads to excessive price volatility Cai et al, 2019). On the other hand, buy herding leads to permanent price impact, which aids with price discovery.

Lantushenko and Nelling (2017) investigated herding of REITs at a property-type level, the study found the prevalence of herding behaviour by institutional managers at a property-type level. The sample data constituted of a vast and broad range of institutional investors which included commercial banks, mutual and pension funds, and insurance companies. The data was made up of a total of 1 697 institutions trading in a given quarter. Data was sources from 3 resources: prices and returns for equity REITs come from the Center for Research in Securities Prices (CRSP). REIT property-type classifications come from NAREIT, quarterly changes in holdings of institutional investors for each REIT from the Thomson financial database. The sample period was from the first quarter of 1993 to the last quarter of 2011, making it a total of 76 quarters. In 1993 the Revenue Reconciliation Act was instituted which altered the invest clientele in REITs stock (Lantushenko and Nelling, 2017). The herding behaviour was detected by measuring buying demand of each property-type in a given quarter, the demand significant and corresponded positively over consecutive quarters (Lantushenko and Nelling, 2017).

Lantushenko and Nelling (2017) found that 75% of the previously mentioned correlation and correspondence is attributed to institutional managers pursuing lagged trades of others, though they normally pursue lagged trades of their own into the same stocks. It is more likely that they would pursue lagged trades of others in different stocks in same property type (Lantushenko and Nelling, 2017). The authors stated that herding by REIT investors may be at the property-type level, as opposed to at the individual stock level. Furthermore, it is shown that REITs use positive feedback trading strategies and momentum trading is neither the primary driver of property-type herding behaviour nor a profitable trading strategy. There was no indication of return reversals during the sample period which denotes that correlated trading information is a driver of herding behaviour in REITs.

5.2.2 Symmetric Herding

The CSSD model is based that analyse herding towards market consensus developed by (Christie and Huang, 1995). The study investigated CSSD of investors around the U.S. equity market during periods of bull and bear market conditions (Christie and Huang, 1995). When rational asset pricing processes prevail, there is an anticipated increase in dispersion as individual returns move away from the equity market return as individual stocks are divergent in their response to market changes (Christie and Huang, 1995). The CSSD of returns is a measure of dispersion as a result of herding behaviour and its resultant effect on the market (Christie and Huang, 1995). “Dispersions quantify the average proximity of individual returns to the mean”, (Christie and Huang, 1995, P32). Further, “they are bounded from below at zero when all returns move in perfect unison with the market, as individual returns begin to vary from the market return, the level of dispersion increases", (Christie and Huang, 1995, P32). Christie and Huang (1995) aimed to test for herding behaviour when herding is most likely to occur and look at price implications of herding by evaluating if equity returns reveal the presence of herding.

Daily and monthly returns were pulled from the Center for Research in Securities Prices. The CRSP sample data constituted firms with ordinary common shares. The daily data came from NYSE and AMEX firms between July 1962 and December 1988, the monthly data came from NYSE firms between December 1925 and December 1988.

The empirical results purport that dispersions increase more largely in the up market in comparison the down market (Christie and Huang, 1995). The study also found that the marginal increase in dispersion in the down market is predicted by the rational asset pricing model and not herding behaviour (Christie and Huang, 1995).

Vidal-Tomása et al (2019) examine herding behaviour and the cryptocurrency market through two models that analyse return dispersions, namely CSSD and CSAD models. The data was comprised of 65 cryptocurrencies which were sourced from the BraveNewCoin database between January 2015 and December 2017. Herding behaviour was not observed as shown by the significantly positive coefficients meaning that large price movements in the tails of the distribution are not predicted by herding behaviour but rather predicted by the rational asset pricing model.

The COVID-19 outbreak saw the crash of share prices around the globe and lowered the effective transmission of market information in Asian capital markets (Jiang et al, 2022). An investigation of herding behaviour set off by the COVID-19 pandemic in six Asian equity markets (Japan, South Korea, Taiwan, Mainland China, Hong Kong and Singapore) found that a global crisis fuels market fear and herding more especially in equities with high idiosyncratic volatilities (Jiang et al, 2022). Daily stock prices of the six Asian stock markets from the wind database between before and after the COVID-19 pandemic, from February 2019 to January 2020, and from February 2020 to January 2021, respectively. There was no significant difference in the CSSD movements before and after the pandemic, the CSSD are negatively associated with the pandemic markers, herding was detected then (Jiang et al, 2022).

5.2.3 Mixed Herding

The CSSD method developed by Christie and Huang (1995) predates CSAD model by Chang et al. (2000), which is also used to capture herding behaviour. Both models are derived from CAPM. Chang et al. (2000) sought to investigate how investors in different equity markets such as Taiwan, Hong Kong, the U.S., Japan and South Korea make investment decisions. The study detected little to no evidence of herding behaviour in developed markets; however, herding behaviour was detected in the emerging markets (Chang et al, 2000).

Daily stock data was collected from CRSP for U.S. firms and the equally weighted market index and year end market capitalizations between January 1963 and December 1997 for all NYSE and AMEX firms. The Asian daily price returns and equally weighted index return were sourced from the Pacific-Basin Capital Markets Research Center tapes of the University of Rhode Island as follows: Japan and Taiwan (January 1976 to December 1995), South Korea (January 1978 to December 1995) and Hong Kong (January 1981 to December 1995).

Chang et al. (2000) developed the methodology to measure dispersion in international markets, the model reveals how the rational pricing model predicts that equity return dispersions increase aa market returns increase but also have a linear relation. Should investors ignore their information when large price movements occur and behave in accordance with the market, the increasing and linear association will cease (Chang et al, 2000).

The study found that the REITs market circumvents the potential effects on economic policy uncertainty. Further, there is evidence of market-wide spurious herding behaviour and information demand, and supply reveal rational stance by REITs' investment behaviour (Chang et al, 2000). The empirical results purport that when there are large price movements, the U.S. and Hong Kong equity return dispersions increase in a linear fashion which predicts that there is no herding (Chang et al, 2000). The two emerging countries (South Korea and Taiwan) exhibit a non-linear association between their equity return dispersions and the market price movements. This is to say the return dispersions increase at a decreasing rate or decrease at an increase rate in the absolute value of the market return (Chang et al, 2000). The rate of increase in return dispersions of the CSAD model as a proxy of the aggregate market return is large when in the up market as compared to the down market across the five countries (Chang et al, 2000). This observation supports directional asymmetry nature of stocks, where generally stocks act promptly to negative macroeconomic announcements, but small stocks show a slow reaction to positive macroeconomic announcements (Chang et al, 2000).

Aharon (2021) embarked on a study to explore the relation between market sentiment and herding behaviour. The study sought to provide evidence of pronounced herding behaviour during periods of fear and uncertainty in the market. To investigate the interactive relation between market uncertainty and herding behaviour, the study made use of the CBOE's Volatility Index (VIX, hereafter) which is a conventional gauge for investor fear, uncertainty and sentiment. The data comprised of 10 size-ranked portfolios made up of stocks that trade on the NYSE, NASDAG and AMEX from the Kenneth French's website, and historical daily data of the VIX from the CBOE website. The study period ran over a period of 30 years from January 1990 to April 2019. The CSAD model was used to detect herding behaviour caused by market sentiment, this evidenced by the non-linear association between the dispersion of returns and market returns were high when movements in the VIX were larger (Aharon, 2021). The quantile regression test showed that the VIX impacts herding behaviour in the highest quantiles as well as in nearly all of the quantiles of the CSAD returns (Aharon, 2021).

The exploration found significant evidence of herding throughout the different subgroup of the size-ranked portfolios, and asymmetric herding feedback to up and down-market movements (Aharon, 2021). The study further indicated that market uncertainty is more prone in small to mid-sized portfolios than in large portfolios (Aharon, 2021).

Youssef (2022) uses the CSAD model to explore herding behaviour in the commodity market from a static and time-varying standpoint. The commodities in question include energy, industrial metals, precious metals, grains food, and livestock. Furthermore, the authors test if oil prices and financial indicators leads to herding behaviour in the commodities market. Daily data was sourced from Energy Information Administration and the Thomson-Reuters DataStream databases from 2003 to 2017 totalling 3736 observations.

The initial results showed no herding behaviour across the commodities markets; however, the time-varying approach detected herding behaviour in most of the commodity sectors especially during and after the global financial crisis (Chang et al, 2000). Oil prices were shown to significantly drive herding behaviour in the energy submarket, the major exchange rate drives herding in the industrial metals submarket (Chang et al, 2000). Finally, the U.S. stock market has very little influence on herding in the energy and industrial metals submarkets (Chang et al, 2000).

There has been a significant interest in the study of herding behaviour in the cryptocurrency market, due to its popularity, performance and volatility (Vidal-Tomás et al, 2019). Most literature on digital currencies focuses on the main digital currencies, Vidal-Tomás et al (2019) studied herding amongst large and small cryptocurrencies and finds that small cryptocurrencies herd with the large cryptocurrencies.

Sixty-five cryptocurrencies from the BraveNewCoin database between January 2015 to December 2017 to test herding behaviour within the cryptocurrency market (Vidal-Tomás et al, 2019). The empirical results of the CSAD regression show that the cryptocurrency markets herd during the down market though there is no evidence of herding with the generalized static CSAD approach. This brings forth the asymmetric nature of herding behaviour (Vidal-Tomás et al, 2019).

5.3 Modelling

5.3.1 Overview

The commonly used herding models are (i) the LSV model, (ii) CSAD of returns and (iii) CSSD of returns. This study adopts the mentioned models for the main analysis and validation of herding behaviour.

5.3.2 The LSV Model

Lakonishok et al. (1992) presented the LSV model of measuring herding as;

$$H(i) = \left|\frac{B(i)}{B(i)+S(i)-p(t)}\right| - AF(i) \tag{5.1}$$

where $H(i)$ is herding measure for a given stock in a given quarter, $B(i)$ is the number of money managers who increase their holdings in the stock in the quarter (net buyer), $S(i)$ is the number of money managers who decrease their holdings (net seller), $p(t)$ is the expected proportion of managers buying in the quarter relative to the number active, and $AF(i)$ is an adjustment factor. Lakonishok et al. (1992) defined AF as $\left|\frac{B}{(B+S)-p}\right|$ under the null hypothesis of no herding; where B, S and p are the same as $B(i)$, $S(i)$ and $p(t)$, respectively. This study defines $AF(i)$ in the same way as in Lakonishok et al. (1992). The authors opined that the LSV model should be used in conjunction with two ratios;

$$D_{ratio(i)} = \frac{[\$buys(i)-\$sells(i)]}{[\$buys(i)+\$sells(i)]} \tag{5.2}$$

where $\$buys(i)$ is total dollar increases by money managers in the given stock-quarter, and $\$sells(i)$ is the total dollar decreases in holdings. The second ratio is;

$$N_{ratio(i)} = \frac{\#buys(i)}{\#active(i)} \tag{5.3}$$

where $\#buys(i)$ is the money managers increasing the holding of the stock in quarter i and $\#active(i)$ is the number of money managers changing their holdings in quarter i. Ratios (1) and (2) are named (i) excess demand in a quarter in monetary value and (ii) excess demand in a quarter in number terms, respectively (Lakonishok et al. 1992).

5.3.3 The CSAD Model

Chang et al. (2000) exemplified that the CSAD model as having both the upward and downward states. Based on the states, the CSAD models are;

$$CSAD_t^{up} = \alpha + \gamma_1^{up}\left|R_{m,t}^{up}\right| + \gamma_2^{up}\left(R_{m,t}^{up}\right)^2 + \varepsilon_t \qquad (5.4)$$

and

$$CSAD_t^{down} = \alpha + \gamma_1^{down}\left|R_{m,t}^{down}\right| + \gamma_2^{down}\left(R_{m,t}^{down}\right)^2 + \varepsilon_t \qquad (5.5)$$

where $CSAD_t$ is the average absolute value (AVD) of each stock relative to the return of the equally-weighted market portfolio, $R_{m,t}$ in period t, and $\left|R_{m,t}^{up}\right|$ ($\left|R_{m,t}^{down}\right|$) is the absolute value of an equally weighted realized return of all available securities on day t when the market is up (down) (Page 1656). The γ_s are co-efficients and ε_t illustrates the error term. Chang et al. (2000) defined AVD as $AVD_{i,t} = |\beta_i - \beta_m|E_t(R_m - \gamma_0)$. On the other hand, Chang et al. (2000) showed that AVD is simply CAPM. This study calculates AVD as CAPM values.

5.3.4 The CSSD Model

The CSSD model can be illustrated in more than one way (See; Chang et al. 2000, and Christie and Huang 1995). This study adopts the CSSD formulation in Christie and Huang (1995) because it is simpler and easier to compute. According to Christie and Huang (1995), the CSSD model is given by the following formula;

$$S = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}} \qquad (5.6)$$

where r_i is the observed return on firm i and $\bar{r}$ is the cross-sectional average of the returns in the portfolio. In order to detect herding during stressed conditions, Christie and Huang (1995), used the following linear regression;

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^u + \varepsilon_t \qquad (5.7)$$

where $D_t^L = 1$, if the market return on day t lies in the extreme lower tail of the return distribution or zero (0) otherwise, and $D_t^u = 1$, if the market return on day t lies in the extreme upper tail of the return distribution or zero (0) otherwise. The upper and lower is defined in relation to $\bar{r}$. According to Christie and Huang (1995), α is average dispersion outside "areas" covered by dummies. The CSSD model in here, is used for the robustness test because of its simplicity.

5.3.5 Finalisation on the Modelling

The traditional and more widely used tests of herding behaviour are the CSSD approach developed by Christie and Huang, as well as the CSAD framework developed by Chang, Cheng and Khorana (CCK) have demonstrated conflicting results which is consistent with the methodological critique of both models (Mand and Sifat, 2021). The phenomenon of herding is not constant over time, and to circumvent this dynamism, time-varying techniques are employed (Mand and Sifat, 2021). Secondly, the CSAD model is a less rigorous approach to detecting herding behaviour because though the CSAD model can capture the nonlinearity of herding behaviour, it cannot capture herding behaviour under varying market regimes (Mand and Sifat, 2021).

Considering the discussions around herding behaviour, it can be surmised that the herding is an indicator of an inefficient and irrational market, making it difficult to employ price valuation methods that are based on sound and rational asset pricing models. The traditional tests for herding behaviour are not void of perfection, however, our study will employ strategies to test and account for the dynamic asymmetry of herding behaviour under different market regimes and ensure robustness. The study has widespread implications for portfolio mangers' hedging strategies and how the construct their portfolios. During periods of uncertainty and herding in capital markets investors do not get great benefit from diversification (Aharon, 2021) investors may use the findings from the study to better mitigate, control and monitor their exposure.

Note that given that the data in this study is on bonds, equities and real estate. This study applies the three models in their original form because analysed indices have distinct features; for example, illiquidity and heterogeneity in real estate, and prevalent liquidity in bonds and equities (See; Kola, 2021).

5.4 Empirical Application

5.4.1 Data

For the data, the study used the top REITs in each of the countries, used market capitalisation (cap) as the measure. Basically, REITs based on the biggest market caps are used, provided data is available on them. The quarterly data is from the 31st of January 2013 to the 31st of December 2021 from Bloomberg terminal. For the U.S., the following REITs are used-Prologis, American Tower, Equinix, Public Storage, Crown Castle, Simon Property Group, Digital Realty, Realty Income, VICI Properties, SBA Communications, Mid-America Apartment and Sun Communities. For the UK-Segro Plc, Land Securities Group Plc, British

Land Company Plc, Unite Group Plc, Derwent London Plc, Tritax Big Box REIT Plc, Big Yellow Group Plc, Safestore Holdings Plc, Lxi REIT Plc, Londonmetric Property Plc, Assure Plc and Primary Health Properties Plc.South Africa-Growthpoint, Redefine, Vukile, Resilient, Hyprop, Equities, Castleview, SA Real Estate, Burstone Group, Attacq, Stor-Age and Fairvest. Taiwan-Cathay No.1 REIT, King's Twon Millerful No1. REIT, Cathay No.2 REIT, Fubon No.2 REIT, O-Bank No.1 REIT and Taiwan Land Development. Note that for calculating herding behaviour, the REIT performances for each country are amalgamated together to form an index. The standardized data provides reliability and replicability of the study. On the academic front, investigation of herding behaviour builds on the ongoing research on herding behaviour, and further shed light on market-wide herding across different geographies, markets and asset classes. The top 12 REITs generally have the highest market capitalizations and trading volumes, making them particularly influential in their markets. Their actions often shape overall market trends and drive herding behavior. Although the study focuses on just a subset, these top REITs represent broader market movements, as they hold a significant share of total market assets and reflect key industry practices. While the research centres on the top REITs, the results can still provide valuable insights into wider REIT market behavior because of the important role these companies play. Future studies could look at smaller REITs to expand the findings and improve generalizability.

5.4.2 Analysis

In presenting the results, this study first presents the analysis of the LSV model. Table 5.1 illustrates quarter herding based on LSV analysis.

Table 5. 1: LSV Results

Year	Quarter	U.S. H(i)	UK H(i)	South Africa H(i)	Taiwan H(i)
1	1	-0.072	-0.091	-0.059	-0.617
1	2	-0.042	-0.11	-0.165	-0.375
1	3	-0.131	-0.04	-0.106	-0.345
1	4	-0.126	-0.052	-0.162	-0.386
2	5	-0.045	-0.066	-0.104	0.278
2	6	-0.013	-0.087	-0.108	-0.509
2	7	-0.029	-0.077	-0.192	0.405
2	8	-0.04	-0.053	-0.098	0.458
3	9	-0.04	-0.046	0.004	0.5
3	10	-0.072	-0.052	-0.188	0.458
3	11	-0.088	-0.05	-0.208	-0.57
3	12	-0.088	-0.1	-0.121	-0.725
4	13	-0.037	-0.076	-0.066	-0.239
4	14	-0.022	-0.058	-0.114	-0.245

Year	Quarter	U.S. H(i)	UK H(i)	South Africa H(i)	Taiwan H(i)
4	15	-0.013	-0.111	-0.116	-0.277
4	16	-0.027	-0.13	-0.123	-0.245
5	17	-0.051	-0.098	-0.014	-0.249
5	18	-0.068	-0.141	-0.076	-0.917
5	19	-0.083	-0.13	-0.085	0.167
5	20	-0.038	-0.115	-0.09	0.633
6	21	-0.041	-0.076	-0.06	-0.212
6	22	-0.04	-0.07	-0.146	-0.311
6	23	-0.059	-0.062	-0.081	-0.272
6	24	-0.158	-0.051	-0.097	-0.158
7	25	-0.091	-0.105	-0.086	-0.151
7	26	-0.045	-0.146	-0.091	0.105
7	27	-0.058	-0.101	-0.054	-0.06
7	28	-0.06	-0.095	-0.095	-0.342
8	29	-0.086	-0.071	-0.17	-0.162
8	30	-0.154	-0.061	-0.066	-0.496
8	31	-0.116	-0.086	-0.045	-0.326
8	32	-0.078	-0.096	-0.063	-0.144
9	33	-0.056	-0.105	-0.109	-0.393
9	34	-0.053	-0.079	-0.103	-0.33
9	35	-0.083	-0.091	-0.091	-0.307
9	36	-0.054	-0.094	-0.083	-0.362

Note: This table includes the herding measure H(i) values for each market (U.S., UK, South Africa, Taiwan) across different quarters and years.

It was expected as per the LSV results in table 5.1 that herding would be positive based on Lakonishok et al. (1992). However, the LSV results showed negative herding throughout the study period for the U.S., UK, South Africa and generally in the Taiwan REIT (except quarters 5, 7, 8, 9, 10,19, 20 and 26) indices. The positive herding observed from the Taiwan REIT coincides with the exponential rise (from June 2014 to June 2015) and the crash (from June 2015 to February 2016) of the Chinese stock market whose linkages to the Taiwan market has been shown (Yousaf and Hassan, 2019). According to Lakonishok et al. (1992) an adjustment factor greater than zero is indicative of no herding, the REIT indices also had an adjustment factor greater than zero. The results detected evidence of negative herding (or anti-herding behaviour). Coskun et al. (2020) noted negative herding between low and high volatility regimes to positive herding during crash regime for REITs, negative herding is observed under volatility regimes then positive during crash regime. It is important to note that the tool used in the study is a static herding tool whereas Coskun et al. (2020) used is a dynamic tool. Over the time series, for first year, herding starts by increasing from the first quarter to fourth quarter. Then, from the second year and thereafter, for the first quarter to the fourth quarter, herding starts from a high node to lower node. Probably, the pattern is due to first being momentum, be volatility, be high first thereafter, decreases as the more information comes out to the market on the herding processes. The latter phenomenon is consistent with the volatility theory.

The REIT indices illustrate negative herding while stocks, as in Lakonishok et al. (1992) show positive herding. The negative herding is due to diversification, which should be present given indices have a number of stocks as constituencies, in stocks, positive herding increases risk, which should require further risk mitigating strategies. The latter finding is novel in relation to the findings in Lakonishok et al. (1992). According to the current body of knowledge, this is the first investigation that confirms that indices lead to negative herding while stocks lead positive herding as per prior studies such as Lakonishok et al. (1992). That is, index herding should be applied as part of mitigating against the risk in global markets. On the other hand, Kola (2021) confirmed that the presence of listed real estate in investing offers opportunities to create other strategies and/or uncommon performance outcomes.

Just like in Lakonishok et al. (1992), this study proceeds and explore aggregates measures; standard deviation and standard error, in order to ascertain whether the individual quarter are the same and/or different to aggregate performance for the given period. Table 5.2 shows the aggregate calculated measures.

Table 5. 2: Aggregate Measures for LSV Analysis

Parameter	U.S.	UK	South Africa	Taiwan
Mean	-0.065	-0.085	-0.101	-0.187
Median	-0.057	-0.087	-0.096	-0.260
SD	0.036	0.028	0.047	0.356
SE	0.006	0.005	0.008	0.059

Note: U.S. is for the United States of America and the UK is for the United Kingdom. SD is standard deviation and SE is standard error.

The aggregate measures provided (mean, median, standard deviation (SD), and standard error (SE)) display the patterns of herding behavior in the four markets (U.S., UK, South Africa, and Taiwan). The mean values are as follows: U.S.: -0.065, UK: -0.085, South Africa: -0.101 and Taiwan: -0.187. The mean values represent the average herding measure across time for each region. A more negative value indicates stronger herding behavior (i.e., investors are moving in a more uniform direction, either buying or selling together). Taiwan shows the strongest herding behavior on average (-0.187), suggesting investors tend to follow each other more closely. South Africa also demonstrates notable herding (-0.101), with a higher average than the U.S. and UK. The U.S. shows the least herding (-0.065), suggesting a relatively lower degree of investor clustering.

The median values, which represent the middle point of the distribution, provide further insight into the typical level of herding. Taiwan again stands out, with the lowest (most negative) median value (-0.260), reinforcing the notion that herding is particularly strong in this market. The UK and South Africa have similar medians, suggesting relatively similar levels of herding behavior. The U.S. has the highest (least negative) median value, aligning with its lower overall herding level.

The standard deviation measures the variation or spread of the herding measures. Higher SD values indicate greater volatility in herding behavior. Taiwan has a significantly higher SD (0.356), indicating that herding behavior fluctuates more drastically in this market. Investors may alternate between periods of strong herding and weaker clustering. South Africa also shows higher variability (0.047), suggesting fluctuations in investor behavior. The U.S. and UK exhibit relatively lower SDs (0.036 and 0.028), indicating more consistent levels of herding over time.

The standard error reflects the precision of the mean as an estimate of the true herding behavior. Taiwan has the highest SE (0.059), suggesting that the estimate of the mean herding behavior is less precise due to the large variability in the data. The U.S., UK, and South Africa all have relatively small SEs, meaning the mean herding measure for these markets is more reliable.

Taiwan stands out as a market with both the strongest herding behavior (lowest mean and median) and the greatest variability (high SD), indicating that investor behavior in this region is not only more uniform but also more erratic. South Africa also shows notable herding with moderate variability, reflecting less consistent but still strong clustering of investor actions. The U.S. and UK display lower levels of herding overall, with more stable and predictable behavior compared to the more volatile herding patterns observed in Taiwan and South Africa.

These findings suggest that herding behavior is more pronounced in emerging markets (Taiwan, South Africa), with more stable and less intense herding in developed markets (U.S., UK). This could be attributed to differences in market maturity, investor behavior, and regulatory environments.

Table 5. 3: The CSSD Results

U.S.					UK				
	Coefficient	**Std. Error**	**t-Stat**	**Prob.**		**Coefficient**	**Std. Error**	**t-Stat**	**Prob.**
Intercept	0.020	0.001	33.485	0.000000%	**Intercept**	0.020	0.000	44.132	0.000000%
Up	0.022	0.003	8.317	0.000000%	**Up**	0.022	0.002	11.248	0.000000%
Down	0.018	0.003	6.666	0.000000%	**Down**	0.016	0.002	8.047	0.000000%
R-squared	0.188				**R-squared**	0.281			
S.E of Regression	0.012				**S.E of Regression**	0.009			
Sum of Squares Reg.	0.016				**Sum of Squares Reg.**	0.015			
Sum of Squares Resid.	0.071				**Sum of Squares Resid.**	0.039			
F-statistic	54.091				**F-statistic**	91.208			
Diff. of Squares	466.000				**Diff. of Squares**	466.000			
South Africa					**TAIWAN**				
	Coefficient	**Std. Error**	**t-Stat**	**Prob.**		**Coefficient**	**Std. Error**	**t-Stat**	**Prob.**
Intercept	0.024	0.001	31.212	0.0000000%	**Intercept**	0.007	0.001	9.055	0.000000%
Up	0.044	0.003	12.876	0.0000000%	**Up**	0.020	0.004	5.738	0.000002%
Down	0.037	0.003	10.751	0.0000000%	**Down**	0.032	0.004	8.908	0.000000%
R-squared	0.365				**R-squared**	0.158			
S.E of Regression	0.016				**S.E of Regression**	0.018			
Sum of Squares Reg.	0.068				**Sum of Squares Reg.**	0.036			
Sum of Squares Resid.	0.119				**Sum of Squares Resid.**	0.193			
F-statistic	133.908				**F-statistic**	53.664			
Diff. of Squares	466.000				**Diff. of Squares**	572.000			

Note: that U.S. is the United States of America and UK is the United Kingdom.

The first part of the analysis involves running an CSSD model which provides insights into the degree of similarity (indicative of herding behaviour) or divergence (rational behaviour) in the U.S., UK, South African and Taiwanese REIT markets. As per Christie and Huang (1995) two hypotheses in the extreme tails were tested through a regression model where the up and down variables are proxies for the bull and bear markets.

The (up and down) coefficients are positive for all four geographies (the U.S., the UK, South Africa and Taiwan). The t-statistics of β_1 and β_2 are greater than 2, thus verify the coefficients' soundness (Christie and Huang, 1995). Therefore, dispersions are higher than average when there are big movements in prices (Christie and Huang, 1995). These results are consistent with the predictions of rational asset pricing and contradict the predictions of herd behavior.

The p-values of the coefficients (up and down) and the intercept are all very close to zero, which indicates that the intercept, up, and down are statistically significant predictors. The R^2 values of 0.188 (U.S.), 0.281 (UK), 0.365 (SA) and 0.158 (Taiwan) indicate that approximately 18.8%, 28.1%, 36.5% and 15.8% of the variance in the dependent variable is explained by the independent variables in the model. The missing 81.2%, 71.9%, 63.5% and 84.2% are explained by something else.

In all the REIT markets, the CSSD regression indicates that the REIT markets appear to behave rationally, with no signals of herding. The CSSD increases in bull and bear markets, thus investors do not herd towards the market signals. This surprising given that South Africa and Taiwan are emerging markets, and it is expected that they should herd (See; Kola 2021). Potential reasons for the latter finding could be that competition among emerging markets (See; Rani and Furrer 2021) and quick convergence of currencies of emerging and emerged markets (See; Costa et al. 2024).

Table 5. 4: The CSAD Results

U.S.					UK				
	Coefficient	**Std. Error**	**t-Stat**	**Prob.**		**Coefficient**	**Std. Error**	**t-Stat**	**Prob.**
Intercept	0.012	0.001	19.658	0.000000%	**Intercept**	0.011	0.001	22.400	0.000000%
Squared Market Return	0.227	0.183	1.239	21.590111%	**Squared Market Return**	0.938	0.285	3.295	0.106121%
Absolute Market Return	0.265	0.033	8.091	0.000000%	**Absolute Market Return**	0.237	0.031	7.594	0.000000%
Market Return	0.015	0.013	1.134	25.719166%	**Market Return**	0.031	0.011	2.817	0.505884%
R-squared	0.416				**R-squared**	0.493			
S.E of Regression	0.008				**S.E of Regression**	0.006			
Sum of Squares Reg.	0.021				**Sum of Squares Reg.**	0.018			
Sum of Squares Resid.	0.029				**Sum of Squares Resid.**	0.018			
F-statistic	110.368				**F-statistic**	150.800			
Diff. of Squares	465.000				**Diff. of Squares**	465.000			
South Africa					**TAIWAN**				
	Coefficient	**Std. Error**	**t-Stat**	**Prob.**		**Coefficient**	**Std. Error**	**t-Stat**	**Prob.**
Intercept	0.012	0.001	17.013	0.000000%	**Intercept**	0.002	0.000	12.997	0.000000%
Squared Market Return	-0.118	0.203	-0.583	56.048352%	**Squared Market Return**	-0.510	0.017	-30.890	0.000000%
Absolute Market Return	0.485	0.036	13.584	0.000000%	**Absolute Market Return**	0.697	0.012	57.466	0.000000%
Market Return	0.033	0.014	2.337	1.985790%	**Market Return**	0.022	0.009	2.437	1.510092%
R-squared	0.594				**R-squared**	0.933			
S.E of Regression	0.010				**S.E of Regression**	0.002			
Sum of Squares Reg.	0.062				**Sum of Squares Reg.**	0.046			
Sum of Squares Resid.	0.043				**Sum of Squares Resid.**	0.003			
F-statistic	226.759				**F-statistic**	2663.612			
Diff. of Squares	465.000				**Diff. of Squares**	571.000			

Note: that U.S. is the United States of America and UK is the United Kingdom.

The second part of the analysis involves the CSAD model which is a more rigorous tool compared to the CSSD model and detects herding with better precision.

The β_3 is the coefficient for the squared market return (Rm^2) and is used to detect herding, South Africa and Taiwan exhibit negative coefficients -0.118 (SA) and -0.510 (Taiwan). The t-statistics for the squared market returns in South Africa and Taiwan are less than 2, and the p-value for South Africa (56.048%) rejects the null hypothesis for herding in the South African REIT market. However, the p-value for Taiwan is close to zero making the observed herding behaviour statistically significant in the Taiwanese REIT market. The R^2 values of 0.594 (SA) and 0.933 (Taiwan) indicate that approximately 59.4% and 93.3% of the variance in the dependent variable is explained by the independent variables in the model.

The U.S. (0.227) and the UK (0.938), however, presented positive β_3 coefficients. The t-statistics for the squared market returns in the U.S. is less than 2, and greater than 2 in the UK. The p-value for the U.S. is above zero indicating insignificance, whereas the UK presents a low p-value (0.106%) making its observations statistically significant.

The CSAD has observed herding in the developing REIT markets (South Africa and Taiwan) compared to the CSSD model that suggests an overly rational South African and Taiwanese REIT markets, though the observations were not significant with the South African REIT market. The U.S. and UK markets were found to comply with rational behaviour.

5.5 Conclusion

The findings of this study are as follows. First, based on the LSV model, real estate indices herd negative direction, which is different to other capital markets instruments. Unsurprisingly, there is standard error in the LSV modelling and the error is more evident in emerging markets-Taiwan and South Africa. Second, the CSSD results reveal that individual selected REITs do not herd and the latter revelations might be due to the thinner individual REIT information asymmetry in relation to real estate indices. Third, contrary to the CSSD results, the CSAD results reveal herding in emerging markets. The latter episode might be due to computational structuring of CSSD versus CSAD model. CSAD is better at capturing non-linear herding behavior, particularly during extreme market conditions, because it incorporates squared and absolute market returns. This helps detect herding when investors overreact to significant market changes.

CSSD, being linear in nature, might miss out on these non-linear patterns and is more focused on smaller market movements. Hence, CSSD may show lower herding tendencies in markets with more frequent extreme events, such as Taiwan. The higher R-squared values in CSAD results suggests that this model explains a larger portion of the variance in herding behavior compared to CSSD, indicating that the CSAD model provides a more comprehensive understanding of herding behavior, especially in more volatile or emerging markets (South Africa, Taiwan). In markets with high volatility or where investor behavior shows sharp clustering during extreme conditions, CSAD is the preferred model as it accounts for non-linearities. For more stable markets, CSSD might still be appropriate to detect herding during normal trading periods.

The CSAD model's ability to detect non-linear herding behavior explains the higher herding measures compared to CSSD, especially in volatile markets like Taiwan and South Africa. These differences highlight the importance of using both models to capture a full picture of herding dynamics. CSAD provides a more sensitive measure of herding under extreme market conditions, while CSSD might be more suited to detecting herding in stable environments. Therefore, the use of both models allows for a more nuanced understanding of herding across different market conditions.

The implications for this study are first, real estate has diversification traits and it should be treated as such-diversified asset. Second, in the context of real estate, herding is easier to pick up from indices than from listed real estate investment vehicles, such as REITs. Finally, emerging markets usually herd to emerged markets.

6 Conclusions, Recommendations and Further Work

6.1 Overall Conclusion

This thesis investigated market wide herding, where selected emerged financial markets (i.e., U.S. and UK) are compared and/or contrasted with emerging financial markets (i.e., Taiwan and South Africa). The theme, market wide herding is nothing new in the broader capital markets but in the context of the real estate industry, such empirical studies are very thin indeed. In order to disentangle real estate market wide herding, this study focuses on the three inferences. First, index herding behaviour of emerged markets versus emerging markets. Second, volatility patterns during herding of bonds, equities and real estate. Finally, using commonly used and accepted herding models to test herding in the real estate industry.

The first hypothesis confirms that herding among bonds, equities and listed real estate exist and moreover, the herding behaviour is linked to governmental relationships. The second hypothesis shows that the volatility risk herd into emerging markets from the emerged markets. Third, this hypothesis exemplifies that herding exists in real estate and herding is model sensitive. As a matter of principle, real estate herds in an opposite direction to its market.

6.2 Applied Techniques

The first hypothesis used principal component analysis and the VAR model. The two models are used without any alterations for the first hypothesis. The second hypothesis uses (i) GARCH (1,1), (ii) VAR and (iii) Markov-regime switching model. The models used for the second hypothesis are used in their original forms. The final hypothesis uses the LSV, the CSAD and the CSSD model, without any structural changes in any of those models.

6.3 Findings on the Hypotheses

6.3.1 Findings on Behaviour of Indexation

The first hypothesis compares and/or contrast market wide herding of bonds, equities and real estate in the U.S., the UK, Taiwan and South Africa. The results confirm similar market wide herding behaviour across those three indices across those four selected financial markets. However, South Africa presents a unique picture-South Africa has its own uncommon herding behaviour.

6.3.2 Findings of Volatility Applications

The second hypothesis is centred on volatility herding patterns of bonds, equities and real estate. The GARCH(1,1) results show reactions and persistence of volatilities that are statistically significant. When the empirical work is lagged, either out-of or in-sample, the same earlier findings still remain for this hypothesis.

6.3.3 Findings of Irrational Conducts

The third hypothesis uses commonly used herding models to detect herding, both for the market and for selected REIT stocks. Fundamentally, the results confirm that herding is commonly found in indices than in selected REIT stocks. In principle, herding is model sensitive.

6.4 Future Implications

From the first hypothesis, given the interconnectedness between bonds, equities and real estate, and the implication is that appropriate quantitative strategies should be created such that intra-related risks are minimised at all times. Then, on the second hypothesis, given that information asymmetry leads to herding, when investing in securities where information asymmetry is inherent, financial engineers should craft strategies that appropriately account for information asymmetry. Finally, real estate has diversification benefits; therefore, real estate in a portfolio should be used as part of wider diversification purposes. The latter finding is nothing new as Guedj et al. (2021) confirmed that the inclusion of real estate in an investment portfolio leads to diversification in the same portfolio.

6.5 Future Research Areas

- Intra-and-Trans Atlantic Herding

This study used selected countries, which exclude South America and Oceania among geographies. It will be insightful to roll over this investigation using the same principles to non-listed geographies in this study.

- Multiple Asset Classes Herding

In this thesis, the laboratory is bonds, equities and real estate. Other capital markets such as commodities and currencies are excluded, and the inclusion of excluded asset classes is worth every investigation in the context of herding behaviour.

- The Effects of Information Asymmetry

According to this study, this is the first study that illustrates that prevalent information asymmetry leads to negative herding in the real estate. And the question is, is it only herding? The latter question will be answered by the future research.

- Diversifiable Nature of Real Estate

The diversification benefits inherent in real estate are nothing new but in the context of herding, in particular real estate, it is untested territory. The question is, is there anything further than negative herding of real estate during herding process?

- REIT Portfolio Size during Herding

So far, this thesis confirms herding from indices, and nothing from stand-alone REITs. Given that this study used countable REITs from each of the selected countries, then, the question is, non-herding in REITs, is it due to size and/or number of sampled REITs?

6.6 Recommendations

- Appropriate quantitative strategies should be designed such that negative herding from real estate is well accounted for.

- Stand-alone REITs in the context of herding, should be handled differently to real estate indices.
- Given that information asymmetry is evident in real estate, when modelling volatility, significant information asymmetry should be well accounted for, in used financial models.
- The VAR results confirm startling, integration between the four geographies; therefore, these four countries (i.e., U.S., UK, Taiwan and South Africa) should explore creating amalgamated indices made up of constituents from those four countries; in particular bonds, equities and real estate.
- Real estate should be used for diversification reasons in portfolios.

6.7 Limitations of this Study

The following limitations have been identified in this study:

- The study is limited to only two developed markets and two emerging markets.
- Because REIT markets that will be studied in the emerging markets may be newly established, the study period may be a decade at maximum.
- The techniques used will not be able to detect the type of herding, intentional or irrational, that exists in the varying markets.
- The study will be limited to market-wide herding behaviour.

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