SIGNIFICANCE OF INFRASTRUCTURE INVESTMENTS IN EMERGING MARKETS TO INSTITUTIONAL INVESTORS

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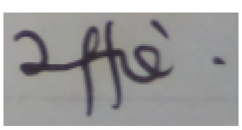
Signed: …  ………………..

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DEDICATION

To my lovely wife, Ronica and my amazing kids Kunashe and Daryl.

ABSTRACT

The worldwide financial crisis of 2007/8 and the subsequent economic slump led to significant funding and solvency challenges for institutional investors as their financial positions were adversely affected. The former institutional investors' investment 'safe haven', being real property/estate, was one of the catalysts for the 2007/8 crisis as the real estate market experienced substantial losses. These experiences altered institutional investors' perceptions towards their traditional asset and portfolio allocation strategies. In an attempt to avoid poor returns and excessive volatility from real estate, bonds and money market instruments, institutional investors are now in a new drive to diversify and supplement their core assets. As a result, institutional (and individual) investors are on the hunt for better yields, diversified portfolios, and inflation hedged returns so that they can meet their long term inflation-indexed liabilities and remain afloat.

Infrastructure sector investments, given their theoretical narratives and attractive investment characteristics qualify to be the new investment niche and appropriate for long term institutional investors. This claim to the attractiveness of infrastructure investments can be rejected or shelved if empirical analysis of infrastructure investment features yields contrary results as the attractive risk-return profile of infrastructure investments might be 'illusory'. The illusion is amplified by the differences in infrastructure investments in developing and developed markets.

This thesis evaluated the economic or financial intrinsic infrastructure investment features to ascertain if institutional investors (in their hunt for new investment avenues), can derive value from the same in emerging markets where the infrastructure gap is high and the infrastructure market still developing. Academic studies on infrastructure investments in emerging and developed markets are scant. The few available academic studies applied very basic statistical measures on the subject matter. The present study adopted, portfolio optimization approach, risk-adjusted return measures, linear and non-linear autoregressive distributed lag (ARDL) models, panel ARDL as well as EGARCH and GJR-GARCH models to achieve the set objectives. As such, the study makes notable contributions to the body of knowledge by applying appropriate econometric models using emerging nations as a case.

The results indicated that unlisted or private infrastructure securities can amplify portfolio returns and dampen portfolio risk. The significance of infrastructure investment to institutional investors is thus limited to enhancing portfolio returns and reducing portfolio risk. The results showed that listed or exchange traded infrastructure's risk-return profile is similar to that of real property and general emerging equity market returns in emerging markets. Private and listed infrastructure exhibited different

stochastic and distributional features implying that they can play a complementary role in a portfolio. This implies that investors can hold listed and private infrastructure in the same portfolio without sacrificing portfolio performance.

Listed infrastructure exhibited remote inflation hedging ability on short term basis. All other assets are poor inflation hedges in emerging markets implying that investors must consider other assets which can hedge inflation risk. All the assets under consideration exhibited significant volatility clustering, volatility persistence and leverage effects. GJR-GARCH specification under GED proved to be the optimal volatility model for all assets under study. This implies that corporates in the infrastructure sector (as well as real property and general equity) in developing economies should be prepared to absorb an additional risk premium as lenders are exposed to significant volatility persistence. On the same note, investors should also come up with other sources of liquidity as volatility persistence will increase the cost of providing liquidity in emerging markets.

Investors are recommended to allocate a significant part of their capital to unlisted infrastructure so that they can enhance their portfolio performance and reduce portfolio diversifiable risk. In order to hedge inflation risk, investors are recommended to look beyond infrastructure, real property and the general equity market in emerging markets. Policy makers in emerging companies are recommended to design contracts and concessions which link returns from long term infrastructure returns to inflation rate. On the same note, regulators in emerging financial markets are recommended to come up with policies which dampen the volatility of asset prices which in turn restore investor confidence, thereby attracting long term capital. Investors are encouraged to consider leverage effects when computing their value-at-risk figures and when making investing decisions. Researchers are encouraged to unbundle the infrastructure sector, and emerging markets ‘groups’ when making future studies. On the same note, as data become available and the economic environment changes, inflation hedging capabilities of the assets covered in this study can be evaluated on a longer term basis in different inflation environments.

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BRICS	-	Brazil, Russia, India, China and South Africa
CAL	-	Capital Allocation Line
CPI	-	Consumer Price Index
CSD	-	Cross Section Dependence
DFE	-	Dynamic Fixed Effects
DIY	-	Diversification -Inflation- Yield
EGARCH	-	Exponential Generalized Conditional Heteroscedasticity
GARCH	-	Generalized Conditional Heteroscedasticity
GDP	-	Gross Domestic Product
GED	-	Generalized Error Distribution
GJR-GARCH	-	Glosten-Jagannathan-Runkle Generalized Conditional Heteroscedasticity
MG	-	Mean Group
MSCI	-	Morgan Stanley Capital International
MSE	-	Mean Squared Errors
NARDL	-	Non-linear Auto Regressive Distributed Lag
OECD	-	Organization for Economic Co-operation and Development (OECD)
PARDL	-	Panel Auto Regressive Distributed Lag
PMG	-	Pooled Mean Group
RMSE	-	Root Mean Square Error
SWF	-	Sovereign Wealth Funds

CHAPTER 1

INTRODUCTION

1.0. General introduction

The worldwide financial crisis of 2007/8 and the subsequent economic slump led to significant funding and solvency challenges for institutional investors as their financial positions were adversely affected (Inderst, 2013, Tooze, 2018, Howard, 2019). As noted by Elliot (2010), public pensions in the United States of America (USA) realized a 25% loss in asset value during the crisis period. Institutional investors were ravaged by interest rate risk, market volatility, and inflation risk during the crisis period (Finkenzeller, 2012; Hasbini, 2017). The former institutional investors' 'safe haven', being real property/estate, was one of the catalysts for the 2007/8 crisis as the real estate market experienced substantial losses (Senturk, 2016; Hasbini, 2017; Jang, Song, Sohn & Ahn 2018). These experiences altered institutional investors' perceptions towards their traditional asset and portfolio allocation strategies. In an attempt to avoid poor returns from real estate, bonds and money market instruments, institutional investors are now in a new drive to diversify and supplement their core assets (Burke 2017; Blanc-Brude 2018; Korvasky 2018; Fixsen, 2019). On the same note, investors are naturally on the look-out for attractive new assets in their quest to optimally revise their portfolios. Portfolio rebalancing and revision can also be used as a risk management strategy in a dynamic financial world (Bourgi, 2018).

Infrastructure sector investments, given their theoretical narratives and mouth-watering investment characteristics (such as inelastic demand, long term nature, predictable and stable cash-flows, and inflation hedging ability), seem to be the new investment niche and a savior for long term institutional investors (Courtois, 2013; Korvasky 2018; McConville 2019). This claim to the attractiveness of infrastructure investments can be rejected or shelved if empirical analysis of infrastructure investment features yields contrary results (Caliari, 2015). This is derived from the claim that a professed and attractive risk-return profile regarding infrastructure investments might be 'illusory' and that infrastructure is the new kid on the block, relative to other asset classes. On the same note, United Nations System Task Team (UNTT), (2015) and Paula, (2017) noted that accessing the infrastructure market is not an easy task as information asymmetry, political risk, incomplete markets and structural impediments abound in emerging markets.

Infrastructure provision, ownership and financing is generally in the hands of the national governments, (given the public good nature of infrastructure products and services), multilateral organizations and international banks (Stewart & Yermo, 2012; Yue, 2013; Inderst & Stewart, 2014; Norges Bank, 2015; Nietvelt, 2019). Since the quagmire of the 2007/8 global financial crisis, the austerity measures which followed in Europe, the European debt crisis of 2009, coupled with slow economic growth and the Basel III regulations; national governments, international banks and multilateral organizations have been constrained in extending their financial arms to fund infrastructure needs (Croce & Yermo, 2013; Norges Bank, 2015; Hussain, Jeddi, Lakmeeharan & Muzaffar, 2019). The Basel III bank supervision regulations which were set in 2010 and operationalized in 2013, call for higher capital reserves and liquidity risk standards for banks when making long term investments (Subhanij, 2017, World Bank, 2018b). Such a scenario is amplifying the ever increasing infrastructure funding gap which is well pronounced and acute in emerging markets (Maier, 2017). The infrastructure funding gap might be fertile ground for institutional investors to tap into - provided the returns far out-weigh the risks involved.

Institutional investors are mainly retirement funds, sovereign wealth funds, and insurers on the lookout for moderate, predictable and less volatile long term returns, commensurate with their long term annuity-type liabilities (Courtois, 2013; Geysen, 2018). Institutional investors endowed with 'patient capital' (from long term annuity-type contributions and premiums), are in search for what infrastructure investments can provide narratively (Organization for Economic Co-operation and Development [OECD], 2015; Burke, 2017; Blanc-Brude, 2018). At face value, the link is a natural fit (Reynard, 2018; Willsher, 2018; Hussain *et al.,* 2019). Given the glaring infrastructure needs gap (where investors can commit their resources), and the socio-economic and political importance of infrastructure the world over, the seminal question is now about the ability of the infrastructure sector to offer a better investment habitat or niche, relative to other equivalent assets. This indicates the need to empirically evaluate the role and significance of infrastructure investments to institutional investors, vested with the fiduciary responsibility of capital preservation and meeting clients' needs profitably (Frankhart, 2013; Blanc-Brude, 2014; Caliari, 2015).

Accordingly, this thesis evaluated the role and significance of infrastructure investments to institutional investors, with special reference to emerging markets, where the infrastructure market is developing, the infrastructure gap is huge and economic growth prospects are quite high (Oberholzer, Markowitz, & Pautz 2018). Emerging markets are prone to violent and wild market swings which institutional investors can harness to earn substantial abnormal returns in both the short and long run (Geysen, 2018). This study is one of the pioneer academic studies in the emerging market which applies a robust econometric approach; therefore the results are of critical importance to investors attracted to the infrastructure segment in developing nations when it comes to portfolio revision and combating inflation risk.

This introductory section of the write up briefly covers the background upon which this study is premised. It exposes the literature and methodological gaps from past studies. This section highlights the problem statement, objectives of the study as well as the contributions made by this thesis. Drawbacks encountered in this present study are also outlined in this part of the thesis. Lastly, this introductory chapter links the different chapters of the thesis.

1.1. Background to the study

During the 2007/8 global financial crisis, the failure of the credit markets was more pronounced than in previous recessions (Reddy, 2016). The crisis affected many financial markets including investment markets and real estate. Chen, Mrkaic and Nabar, (2018) in agreement with Reddy (2016), commented that the world-wide crisis of 2007/8 imprinted lasting and significant effects on capital markets and the global economy. Coupled with subsequent weak recoveries in developed markets and rounds of monetary easing, the crisis resulted in global downward pressure on returns, with Barclays aggregate returns missing their average score by far (Bahceci & Leh 2017). As argued by Bahceci & Leh (2017) and Howard, (2019), even with *'Trumpism'* in the United States of America (USA), private and institutional investors appreciate the fact that periods of low growth and high volatility are likely to remain the new normal for some time. Expectedly, Burke (2017) and McConville (2019) commented that post 2007/8 crisis period, investors' (individual and institutional) search for yield, diversification, and defensive alternative assets, gained momentum the world over.

The hunt for alternative assets is driven by the sole need to meet investors' aims stipulated in risk and yield terns profitably. Imrie and Fairbairn (2014) noted that private organizational investors, such as insurers, are anticipated to meet their objectives, which include the need for maximizing returns, smoothing out investment volatilities, and protection against inflation, portfolio diversification, and hedging their liabilities. As such, these investors are looking for alternative assets which can meet the mentioned needs on both the short term and long term basis.

Considering the 'theoretical' intrinsic investment characteristics of infrastructure sector investments, institutional investors seem to be the natural candidates for investment in this sector (Levy, 2017, Blanc-Brude, 2018). Such intrinsic investment features include; inelastic demand, high pricing powers, long term in nature, an inflation linked pricing system (through concessions and agreements) and steady, less volatile returns (Burke, 2017; Reynard 2018; Thompson, 2019). On the same note, Andonov, Kraussl and Rauh (2019) and Bahceci and Leh (2017) indicated that infrastructure investments afford investors with the 'D-I-Y' merits of risk diversification, inflation shielding and better yields or returns tied to stable cash inflows. Narratively, we can call off the hunt for alternative assets, as the answer is in the investors' backyard. However, Bianchi and Drew, (2017) in agreement with Blanc-Brude, Whittaker and Wilde, (2016) argues that listed infrastructure can only offer risk-return profile similar to other investment classes. Thus, it does not warranty a separate analysis. In addressing this issue, this study used both listed and unlisted infrastructure investments.

The glaring and eye-popping infrastructure investment gap in the world over (especially in emerging markets), provides a room which can be utilized profitably by institutional investors, provided they can derive some tangible financial benefits from the same (Thompson, 2019). Institutional investors possess robust financial muscles, expertise, knowledge and economies of scale which they can use to profitably invest in infrastructure, other things being equal (Nietvelt, 2019). Inderst and Stewart (2014) estimated infrastructure needs to be US$80 trillion globally and cumulatively by 2030, (excluding modernization, conforming to green infrastructure and smart technologies). In Africa, the infrastructure gap amounts to USD 130 billion annually (Oberholzer *et al.*, 2018). This gap is amplified if we consider the need to replace old and inefficient infrastructure constructed in the 19th century. In emerging markets, the infrastructure gap is to the tune of USD$1 trillion to keep pace with economic growth (World Bank, 2018a). The infrastructure gap is more than double when considering the 'go green agenda' hailed in the United Nations' Sustainable Development Goals (Maier, 2017; World Bank, 2018a).

Infrastructure investment attributes are attractive and infrastructure needs far outweigh the supply, the seminal question is whether infrastructure investments can live up to their claimed theoretical investment attributes (Caliari, 2015; Wurstbauer & Schafers 2015; Howard, 2019). The seminal question is based on the fact that institutional investors need to fully assess the infrastructure sector like any other asset class and find the economic rationale before diverting their resources from other asset classes into the infrastructure sector (Bourgi, 2018; Oberholzer *et al.*, 2018). In the case where infrastructure investments in emerging markets are failing to add value (better than comparable assets) to investors' portfolios, then pre-crisis portfolio targets may be recommended, pursued and revised, without infrastructure sector investments in mind.

Asset allocation decision must be made using available relevant information. This indicates the need to carry out an empirical analysis of infrastructure sector investment features in emerging economies, where the infrastructure market is still developing, the funding gap is huge and national governments already saddled with surmounting financial, economic, social and political obligations (Blanc-Brude, 2018). As such the behavior of infrastructure investments in emerging markets are likely to be unique given the uniqueness of emerging markets in terms of risk-return profile and political turmoil.

Considering academic research on infrastructure investments, Finkenzeller (2012) and Wurstbauer and Schafers (2015), decried its paucity. Restated, empirical research on infrastructure is regularly restricted to industrial bulletins and not scholarly studies. The few available empirical academic studies were carried out in developed markets in the course of the pre-crisis phase and just after the crisis era. Subsequently, such studies can only give us suggestive evidence as they were conducted during a time when infrastructure was not broadly considered an asset class and investors were barely focusing on it. This is due to the shocks experienced in the capital and real estate markets throughout the credit market crisis of 2007/8, which prompted investors to focus on infrastructure investments, sparking academic interest (Thierie & De Moor, 2016).

Most industrial periodicals covering infrastructure investments unambiguously identify the attractive features of infrastructure investments such as their potential to protect against inflation, and generating superior, less volatile returns (RARE, 2017). As expected, industry publications used basic methods and procedures which can be easily understood by lay investors. This provides for fertile literature and the methodological gaps addressed in this study.

Reverting to empirical studies, Daniel (2016), considering United States of America (USA) data, concluded that infrastructure provides superior returns and enhances portfolio returns compared to other asset classes. At global level, Chhabria, Kohn, Brooks, and Reid (2015), Kempler (2016) and Moss (2014) concluded that global infrastructure performed better than global equities and global bonds. Concurring with these findings, De Bever, Van Nieuwerburgh, Stanton, and Berkeley (2015) and Daniel’s (2016) studies found that infrastructure investments provided better returns and enhanced portfolio returns compared to other asset classes in USA. Similar results were obtained by Panayiotou and Medda (2014) and Oyedele (2015), who used infrastructure indexes from the United Kingdom and Europe. These studies indicate that infrastructure investments are good performance enhancers compared to other equivalent assets.

Risk diversification ability of infrastructure investments was noted by Newell, Peng, and Francesco (2011) using Australian private equity data while Bahceci and Weisdorf (2014) examined infrastructure investment cash inflows in the USA and Western Europe. Deutsche Asset Management, (2017), using global private infrastructure equity, noted a negative correlation between unlisted infrastructure and listed infrastructure, bonds, and global equity, providing the suggestive risk diversification ability of unlisted infrastructure. As such, unlisted infrastructure investments can be used to dampen portfolio risk, according to these studies and industrial bulletins.

Whilst assessing the ability of infrastructure investments to hedge inflation, Rosenberg Real Estate Equity Funds (RREEF) (2008), found evidence of inflation hedging in the US, although hypothesis testing was ignored so as to authenticate such effects. Similar results were obtained by Colonial First State (2009), using data from Australia.

On the contrary, a study by Oyedele, (2015), using UK data, noted a fall in the ability of infrastructure investments to reduce portfolio risk. On the same note, a number of authors indicated the inability of infrastructure to hedge inflation risk. Such authors include; Peng and Newell, (2007) using Australian data, Rothballer and Kaserer, (2012), considering listed infrastructure firms, Rodel and Rothballer, (2012) looking at listed infrastructure, and Bird, Liem, and Thorp (2014), investigating listed and unlisted Australian and US infrastructure markets. An in-depth analysis by Deutsche Asset Management (2017) established that the capability of the infrastructure sector to withstand inflation shocks depends on the sub-sector category in question with regulated assets (such as water and power), providing a better inflation hedge than tolls, and airports.

On the volatility aspect, industrial bulletins by Blanc-Brude (2015) and CBRE Clarion Securities, (2019) highlighted that infrastructure investment earnings are more stable relative to other segments of the economy. Bahceci and Weisdorf's (2014) pragmatic research on infrastructure cash flows in the US and Western Europe discovered that infrastructure investments are more predictable than standard investments. On the same note, Kempler (2016) and Babson (2013) demonstrated that listed infrastructure investments evidenced inferior return-swings relative to real estate and ordinary shares at global level. These studies support the claim that infrastructure investment is less risky or volatile, whilst generating better returns than other comparable assets.

Most of the reviewed studies used bivariate correlation as a measure of risk diversification ability in the developed world (Colonial First State, 2009; Oyedele, 2015; Kempler 2016; Daniel 2016; Deutsche Asset management, 2017). Inflation hedging ability was tested by simply comparing average returns against inflation rates over the period under study (Oyedele, 2015). The application of very basic statistical methods in the available empirical studies opens a fertile methodological gap worth pursuing. This thesis adopted advanced econometric models in evaluating the significance and role of infrastructure investments with specific reference to emerging markets. Specifically, this present study employed better methods and techniques such as the portfolio optimization method, risk-adjusted return measures, panel autoregressive distributed lag (PARDL) and exponential generalized conditional heteroscedasticity (EGARCH) approaches in evaluating the intrinsic features which are claimed to characterize infrastructure assets in developing nations.

In most developing nations, the infrastructure market is still developing and resultantly, its risk-return profile is likely to be different from the one obtained in mature infrastructure markets in developed economies where competition is stiff due to increased deregulation in the infrastructure sector (Gatti, 2019). A focus on emerging markets is necessary, given that the market is a force to reckon with as emerging economies are expected to grow by 5 to 7% per annum over the next couple of years, compared with 2% in developed markets (Moore 2018; Muller, 2018). On the same note, such a growth trajectory will increase the emerging markets' share of global gross domestic product to 45% by 2020, and to approximately 60% within 15 years (Muller, 2018; International Monetary Fund (IMF), 2019). Naturally, as economies expand, more infrastructure investments are necessary for sustainable economic growth, thereby calling for more investors into the infrastructure market. This is an opportunity not to be missed by private investors, provided the narrative investment features of infrastructure investments are a reality. This indicates the need for an empirical evaluation of these claimed investment narratives in emerging markets where the infrastructure gap is dire. Without supporting academic empirical evaluation, the claimed investment attributes cannot be ascertained in emerging markets.

1.2. Problem statement

Generally, the objective of any rational investor is to employ resources optimally and efficiently in order to realize a return high enough to meet his or her investment goals in the short and long run, other things being equal. In efficient markets, rational investors are expected to earn normal returns commensurate with the market risk assumed. Financial markets are at times inefficient as evidenced by significant market volatility, market crises and asset price bubbles. These inefficiencies, coupled with an ever changing economic environment, render the static strategies of an investor obsolete and unprofitable. As such active and dynamic approach to asset allocation strategies is appropriate.

In effect, the lasting effects and experiences of 2007/8 global financial crisis, subsequent depressed market returns, and Basel III and Solvency II regulations, calls for investment policy revision as portfolios which used to be efficient, favorites, optimal and profitable, are no longer efficient. Subsequently, radical portfolio revision is necessary lest large amounts of money might be lost through inefficient asset allocation and investment goals might continue to be ever evasive.

Financial victims of the 2007/8 global crisis included institutional investors as their assets (against maturing liabilities), were grossly eroded, leaving them unable to achieve their investment goals. As a result, institutional (and individual) investors are on the hunt for better yields, diversified portfolios, and inflation hedged returns so that they can meet their long term inflation-indexed liabilities and remain afloat. Narratively, infrastructure investments seem to be the answer and a promising investment 'niche'. Such a narrative is disputable until empirical studies substantiate the claim.

In most emerging markets, infrastructure funding and provision is traditionally in the hands of national governments, multilateral banks and developmental institutions which are now constrained legally, fiscally, financially and politically. This amplifies the ever-present infrastructure gap, giving enough welcoming room for new players, especially institutional investors with ‘patient low cost capital’ and inflation linked long term annuity type liabilities.

Cognizant of the investment fact that an asset allocation decision largely determines the return and risk of any investment, it is important that an evaluation of the value and significance of infrastructure investments to institutional investors be made before any meaningful asset allocation decision is recommended or considered. Such an evaluation provides an insight into the investment features and attractiveness of infrastructure investments to investors.

Past academic studies were done mostly in developed markets using listed infrastructure investments applying basic and elementary statistical approaches such as correlation and graphical analysis. Therefore, this thesis empirically evaluates the claimed investment features of infrastructure investments (listed and unlisted infrastructure) to ascertain if institutional investors (in their hunt for new investment avenues), can derive value from infrastructure investments in emerging and developing economies where the infrastructure gap is high and the infrastructure market still developing. The present study applied advanced econometric approaches using latest data post global crisis of 2007/8.

1.3. Aim and objectives of the study

This present research empirically evaluated the significance and role which can be played by infrastructure investments in developing nations, with special reference to organizational investors. For comparison purposes, investment features of other related asset classes are also evaluated. In the light of this main aim, the following objectives were pursued;

1. To evaluate the portfolio performance enhancing ability of infrastructure investments in selected emerging markets.
2. To determine the portfolio risk diversification ability of infrastructure investment in selected emerging markets.
3. To ascertain the inflation hedging ability of infrastructure returns in selected emerging economies.
4. To assess the volatility behavior of infrastructure investments in selected emerging markets.

1.4. Research questions

Taking the above objectives into account, the following questions were set;

1. Does the addition of infrastructure investments to a risky portfolio improve portfolio returns or reduce portfolio risk disposition in emerging markets?
2. How are infrastructure investments returns and other asset class returns related in emerging markets?
3. How are infrastructure investments returns and actual inflation related?
4. What are the inflation hedging capabilities of infrastructure returns?
5. How does the behavior of infrastructure assets return volatility compare to other asset classes?
6. How does current news impact the future return volatility of infrastructure returns in emerging economies?

For comparison purposes, same questions were formulated considering other related investment assets in selected emerging markets. This comparison ascertains whether infrastructure can stand as a better asset relative to equivalent assets.

1.5. Gap in literature

Literature is laden with studies considering the significance of traditional asset classes to institutional investors (ignoring infrastructure as a new asset classes). Available literature on infrastructure in general is biased towards industrial communiqués not academic studies. The few available empirical academic studies were carried out mostly in developed markets where the infrastructure market is mature. On the same note, only listed infrastructure was mostly considered in these past studies. The available studies were conducted during the pre-crisis phase and just after the crisis era before the introduction of key financial market regulations such as the Basel III and Solvency II. Basic statistical measures such as bivariate correlations and standard deviation were adopted in most these available academic studies. These gaps in literature are addressed in this thesis.

1.6. Contribution of the study

The present research aims to make substantial contributions to the existing body of knowledge. Whereas most of the available studies concentrated on the significance and role of traditional asset classes (like real estate and bonds), the present study went further and considered the role of infrastructure investments as a new attractive asset class. Most studies (skewed towards industrial bulletins) on infrastructure investments concentrate on the ‘narratives’ whereas this study went beyond the narratives and used concrete financial market data to empirically ascertain the significance of infrastructure investments to institutional investors in emerging markets. This provides room for accepting or rejecting beliefs, assumptions, facts or myths derived from infrastructure investments narratives. Such findings and conclusions definitely feed into the asset allocation and portfolio decision making of investors.

Whereas most previous published studies covered mainly developed individual nations, this study covers emerging economies, thus presenting a fertile contribution in terms of geographical coverage. In other words, there is suggestive evidence, mainly from developed markets, on the tangible intrinsic features of infrastructure investments. This study concentrates on evidence emanating from emerging economies thereby providing new insight into what infrastructure investments in emerging economies can offer investors. As expected, the risk-return characteristics of same investments are expected to be different as an investor migrates from developed to developing economies. Such changes are worth noting as investors continue hunting for steady and less-volatile long term returns. Therefore, this thesis makes a phenomenal contribution to the evolving body of knowledge on the subject of infrastructure sector in emerging economies where empirical knowledge on the subject matter is still limited.

Adding onto that, whereas past studies used very elementary measures of portfolio risk diversification ability and measures of risk (such as correlation coefficient and standard deviation), this thesis applied contemporary econometrics methodologies using panel data, volatility models and portfolio optimization, thus making a methodological contribution. With the rise in globalization, information technology and significant capital market integration, the diversification ability of infrastructure assets might be questionable, hence this present empirical analysis provide insight into the same.

It is not only returns that matter in an investment, but also the level of risk assumed. As such, this thesis went a step further and unveiled the volatility aspects of infrastructure like volatility persistence and volatility asymmetry. To the best knowledge of the researcher, no single published article on the intrinsic features of infrastructure has covered the return volatility aspect.

As one of the pioneer studies on infrastructure investments in emerging markets, it serves as a basis upon which future research can hinge. In other words, it propels the debate on infrastructure investments features further by providing new evidence from emerging markets, using better methods and techniques. To add on, past academic studies covered periods before and just after the 2007/8 financial crisis. For the duration of this era, infrastructure investments were scarcely considered by investors and regulations such as Basel III and Solvency II (which affect long term capital sources), were not yet operationalized. This present study was carried out ten years after the crisis, when infrastructure investments were well appreciated and new regulations affecting traditional financiers of infrastructure and institutional investors were in effect. Resultantly, the study gives post crisis, Basel III and Solvency II evidence of infrastructure investment financial features in emerging economies, thereby making a significant contribution in terms of the period during which the research was carried out.

Findings from this research aid regulatory authorities when crafting regulations with the aim of harnessing more funds towards the infrastructure sector in order to reduce the infrastructure gap. On the same note, regulators will be able to formulate executable and investor friendly policies and institutions, bearing in mind what infrastructure investments in emerging markets can and cannot deliver. Designing appropriate policies and institutions would increase capital allocation efficiency in the capital markets. Insights of this thesis aid investors in their asset allocation decisions such that greater value can be attained from their portfolios, thereby enabling them to achieve their objectives. As such, this study has profound implications for regulatory authorities and investors at large.

1.7. Various chapters and how they contribute to the overall integrated argument of the thesis

This thesis focused on evaluating infrastructure sector investment narratives or features so as to ascertain whether institutional investors can derive any value from the sector, given the amplified search of institutional investors for new defensive assets. The need to revise portfolios was necessitated by the world-wide credit market crisis of 2007/8, and the depressed market returns, which resulted in momentous financial damage to many investors and markets across the globe. Pre-crisis period asset allocation and portfolios were no longer optimal or efficient as the financial environment changed tremendously. On the same note, the European debt crisis of 2009 and the market downturn which followed the Brexit referendum of 2016, prompted investors to take a re-look at their portfolios. The ongoing (as of 2019) trade conflict between the US and China is again plunging the markets into disarray and uncertainty. In such a scenario, defensive investments which are lowly correlated with other asset classes are sort after.

Infrastructure sector narratives in developed and mature markets include the sector's ability to generate long term, steady, defensive, predictable, superior, and less volatile, inflation linked returns. These investment features are what institutional investors are actually seeking in their endeavor to achieve their short and long term goals. Given that these investment features are likely to be different in developing economies, this thesis thereby evaluates these investment features in emerging markets. This enables us to draw the much needed empirical evidence from emerging markets to ascertain what can be offered by the infrastructure sector relative to other sectors.

1.8. Linking the chapters

All the chapters in this thesis aimed at evaluating the investment features of the infrastructure sector in emerging markets. Chapters 3 to 5 (presented in empirical research paper format), specifically evaluate the investment features of the infrastructure sector, with special reference to emerging markets. Findings from papers in chapters 3 to 5 indicate whether institutional investors can derive value from the infrastructure sector in emerging economies or not.

Chapter 1- Introductory chapter

This introductory chapter sets the stage upon which the rest of the thesis is built upon. It laid bare the background issues which prompted the need to evaluate the investment features of the infrastructure sector in emerging economies. Given the scant academic literature on the subject matter, the introductory chapter gave a brief review of studies from developed markets. The aim of this brief review was to give a clue regarding investment features obtaining in developed markets. This gives us suggestive evidence as to what to expect from emerging markets. The main aim and sub-objectives of the thesis were also given in the introductory chapter in order to give the scope of the study. Related to objectives, key research questions were also posed. The input of this thesis into the obtainable pieces of information in terms of time frame, methodology, and entities of interest, was also given. Limitations encountered in evaluating the investment features of infrastructure in emerging markets, are also part of the introductory chapter.

Chapter 2- Literature review

Basic definitions and concepts under study were exposed in the second chapter. In order to put the topic into context, this second section of the thesis exposed the descriptive link between institutional investors and infrastructure investments. The aim of the section was to indicate the existence of a natural fit between what institutional investors are seeking and what can narratively be offered by the infrastructure sector. Infrastructure investment features which were evaluated in this study are fully exposed in this chapter. As can be seen in this chapter, the infrastructure narratives in mature infrastructure markets are likely to be different from those existing in developing infrastructure markets. As such, benefits which accrue to the infrastructure sector in developed markets (less volatile, defensive, inflation hedging) might be different from the benefits, (if any) existing in the emerging economies. The conceptual framework, upon which the empirical study is hinged, forms part of Chapter 2.

Chapter 3- Role of infrastructure investments in a risky portfolio in emerging markets

The third chapter of the thesis covers the first two objectives specified in the first chapter. It evaluates the ability of infrastructure sector to earn superior returns, amplify portfolio returns and reduce portfolio risk relative to other asset classes. These investment features are commonly cited in both industrial bulletins and academic studies in developed nations. The evaluation was carried out at two levels, namely individual asset level and portfolio level. The results indicate that the infrastructure sector earned higher risk-adjusted returns than other asset classes; these findings support the claim that the sector generates superior returns. At portfolio level, the ability of a portfolio with infrastructure assets to earn better returns at lower risk levels than a portfolio without infrastructure assets will be in support of the narrative that the sector is a portfolio risk diversifier. Findings from this chapter give the answer as to whether institutional investors can diversify portfolio risk, amplify portfolio returns or get superior returns from the infrastructure sector in developing economies. Such findings either refute or support the infrastructure sector investment features or the claims under evaluation.

Chapter 4- Inflation hedging capacity of infrastructure returns in emerging markets

The fourth segment details the (in)ability of the infrastructure sector to hedge inflation in emerging markets relative to other asset classes. Inflation risk is a serious economic threat to long term investors, hence the need to do a detailed analysis of this investment feature. This infrastructure investment claim was evaluated using linear and non-linear models as well as panel data models. Results indicating that the infrastructure sector can hedge inflation in emerging markets will be a sweetener for institutional investors who are in search of long term inflation linked returns.

Chapter 5- Volatile behavior of infrastructure assets in emerging markets

The fifth chapter highlights the volatile behavior of infrastructure sector returns in comparison with other asset classes. Results from this paper give evidence of whether investors with interests in infrastructure investment in developing nations are exposed to less volatility compared to other sectors. Such evidence will indicate whether risk premiums should be expected by investors and lenders in the infrastructure sector. Evidence of volatility gives a guide as to what aspects should be incorporated by investors when determining value at risk.

Chapter 6- Further analysis of specific research papers

The sixth chapter is actually part of the papers presented in Chapters 3 to 5. Further analysis was necessitated by the fact that journals limit the number of words, pages and tables in a single paper. As such, some aspects and tests were removed from reviewed papers. Resultantly, the sixth chapter gives more detail and information (not given in chapters 3 to 5), in evaluating the claimed investment features of infrastructure in emerging markets.

Chapter 7- Key findings, conclusions, implications and recommendations

The last chapter of this thesis wraps up the study by giving brief highlights of key findings, deductions, inferences and commendations from the papers presented in Chapters 3 to 5. As the papers covered these aspects in detail, the chapter only gives a snapshot per objective. The conclusions indicate the value (if any) which can be drawn from the infrastructure sector in emerging markets. Recommendations to investors, regulatory authorities and further studies based on the results obtained with regard to infrastructure investment features in emerging markets, were part of this last section.

1.9. Limitations of the study

This section of the thesis highlights key shortfalls of this present study. The notable drawbacks are as follows:

Infrastructure is still a developing evolving asset.

In comparison with other asset classes like real estate, derivatives and bonds, infrastructure investments are still in the developmental stages in most emerging markets. As such, it should be kept in mind that whatever is discussed in this thesis is based on a relatively new asset on the block (Furnes, 2019). On the same note, the features of infrastructure investments are therefore likely to pass through some notable changes as the market morphs and mature.

Data availability

Closely related to the first limitation is the issue of data availability in the public and private domains. Data on infrastructure sector performance is very scant the world over, let alone in emerging markets (Lauridsen, Chastenay, & Kurdyla, 2018). This comes in handy when country and company analysis is appropriate. Due to this drawback, this study made use of available (to the public) emerging markets infrastructure sector index data and accessible country specific data.

Time period

Arguably, a ten year period might not be lengthy enough to ascertain the presence or absence of a long run connection amongst variables. One of the variables of interest (private infrastructure equity index) was launched 10 years ago, hence the use of the maximum available data periods. To augment the validity and reliability of the results, daily, monthly and quarterly frequencies were used in this study.

Heterogeneity of emerging markets and number of nations considered

The term, emerging market, refers to economies which are heterogeneous in every aspect with respect to their social, political and economic policies. Due to this lack of homogeneity, country by country analysis might be helpful. Data availability at country level is, however, a chief limitation. In trying to reduce the effect of the homogenization of emerging economies on this research, the study used individual country analysis in one of the papers.

Heterogeneous nature of infrastructure sector

The infrastructure sector is heterogeneous, stretching from economic infrastructure to social infrastructure. As such, sub-sector analysis might offer different and better insights. The only drawback is the unavailability of such data in emerging markets.

Few measures of risk-adjusted return

The use of few risk and return measures such as standard deviation, Sortino ratio and Sharpe ratio in this study might be treated as a weakness by other scholars (thereby questioning the validity of the results and conclusions herein). This is based on the idea that there are so many measures of risk and return which are applicable. However, the measures applied in this study at least covered both categories - the absolute risk measures and the downside risk measures.

Low inflation periods

It must be noted that during the period under study, very low levels of inflation were the norm, as such investors were not worried about inflation risk. In hindsight, we can say investors were not concerned about inflation, but in reality, they were not aware what inflation rates would be in the next period, thus they were on the lookout. In other words, the risk did not materialize but investors need to make sure they are always protected against potential risk.

Preceding performance is never an indication of impending performance

Whilst this is spot-on, we believe the returns over the last 10 years have clearly demonstrated the tangible investment features of infrastructure assets relative to other asset classes. After all, the main aim of this thesis was not to forecast future trends using past trends, but to evaluate investment features in emerging markets using past data.

Scant academic studies

Academic studies on infrastructure as a new asset are very few the world over, let alone in emerging markets. The few available studies are skewed towards developed markets, with little or no reference to emerging markets. This study was therefore carried out as one of the pioneering academic studies on infrastructure in emerging markets, using past academic studies and industrial bulletins from developed markets.

Infrastructure is not a standalone asset class

This is very debatable given that some authors argue that infrastructure cannot be classified as a separate asset class (Blanc-Brude *et al.*, 2016; Bianchi & Drew, 2017). Such authors make their conclusionsc after an evaluation of listed infrastructure only. As such, some authors counter this view (Rothballer & Kaserer, 2012; Howard, 2019). This study made an evaluation on listed and unlisted infrastructure so that valid conclusions are made.

1.10. Chapter summary

This chapter introduced the subject matter under study, highlighting the need for institutional investors to revise their portfolios so as to meet their long term inflation linked liabilities, among other objectives. This chapter exposes the investment features of the infrastructure sector, which can be of great value if realizable. In terms of related literature, this section indicated the scantiness of academic studies of the infrastructure sector the world over, let alone in emerging markets. The rationale of this present study, premised on evaluating the investment features of the infrastructure sector, was laid bare in this chapter. The contribution of this thesis to the body of knowledge in terms of academic studies, methodology, time period and new insights for policymakers and investors, were also discussed. Lastly, limitations of the study such as data unavailability and the heterogeneous nature of emerging markets, which can be a source of further studies, were exposed in the last section of the chapter. The ensuing chapter links institutional investor needs to infrastructure investment features, detailing the routes available for investing in the infrastructure sector in emerging markets.

CHAPTER 2

LITERATURE REVIEW

2.0. Introduction

As each all the papers in presented in this thesis have a section on literature review, this second chapter emphasized the key issues not addressed in these papers. In an attempt to derive insights and suggestive conclusions on the subject under study, this section lays out the review of the scant academic literature and industrial bulletins available mostly in the developed world. This part of the thesis lays bare the conceptual framework around the thesis as well as linking institutional investors' needs and what can be derived from infrastructure investments.

2.1. Definition of key terms

Infrastructure

Due to the heterogeneous nature of the infrastructure sector or assets, infrastructure is more easily identified than defined (Deutsche Asset Management, 2017; Blanc-Brude, 2019). Infrastructure encompasses the physical features, assets, networks and institutions that provide the products necessary for the efficient and optimal functioning of a society (Kempler, 2016). As different concepts and opinions are given in the political, social, economic and financial arenas, infrastructure is defined along the lines of physical characteristics, industrial sectors, economic features, investment attributes and regulatory regime (Inderst, 2013; Bigman & King, 2016). Thus infrastructure is defined basing on the following attributes:

- physical features (roads, bridges)
- industrial, social and economic sectors (transport, energy, sanitation, education)
- economic and intrinsic features (monopolies, high barriers to entry, inelastic demand)
- investment features (stable returns, insensitivity to economic and markets swings, good inflation hedge)

In this thesis, the last infrastructure attribute – investment features – is of interest although the features are derived from the economic attributes of the sector.

Institutional investors

An institutional investor is an organization (private or public) that pools together funds from its members (in the form of premiums or contributions) and makes investments on behalf of the members (Geysen, 2018). These investors are highly respected regarding the resources they manage. They have expertise, an extensive knowledge base and capital, such that they receive preferential treatment in the financial markets (such as lower fees, access to private information) (OECD, 2015). Institutional investors often make payouts (from their investment) to contributors or members for a long period (long term liabilities). Such institutional investors include insurance companies, mutual funds, sovereign wealth funds (SWF), super-annuation funds, and insurance companies. These investors have a long investment horizon concomitant with their long term liabilities (Blanc-Brude, 2018).

Investing

Investing is the commitment of resources (including money, knowledge and expertise) to economic and social activities and/or assets with the aim of generating rewards (economic and social) (Nuveen Asset Management, 2016; Burke, 2017). Governments, individuals, and corporations are the key players in the investment fraternity.

Infrastructure gap

Simply put, the infrastructure gap is the difference between the required or needed infrastructure and the supply of same (Inderst & Stewart (2014). The required infrastructure is estimated based on the current economic growth, urbanization rate, population growth, UN sustainable development goals and the need for repairs and maintenance of existing infrastructure (IMF, 2018).

Inflation hedge

This is an investment or an asset whose value or returns move in lock-step with inflation (Nasr, 2017). Such an investment protects investors from inflation risk in the short or long run (and preferably both). A significant positive correlation between the asset and inflation is thus expected. The ability of an asset or commodity to hedge inflation can be over short or long term.

Volatility

Volatility quantifies the fluctuations of the commodity or security prices over time (Coffie, 2015). In a sense, volatility is a crude measure of risk. This entails that large price fluctuation, is an indication of enormous risk for the asset in question. The main focus in this study is on historical volatility (which is derived from past asset market prices and returns). It is normally measured using standard deviation and beta (Ndwiga & Muriu, 2016).

2.2. Theoretical review

This section outlines the key concepts under study as expounded in industrial bulletins.

2.2.1. Infrastructure investments unpacked

Following the definition of infrastructure above, this study's overall focus is on the claimed investment features of infrastructure in developing markets. The infrastructure market in emerging economies is still evolving, thus it is likely to have different and interesting investment features from those existing in developed nations (Lauridsen *et al.,* 2018). For the purposes of clarity, infrastructure investments or assets are normally separated into economic and social categories as presented in Table 2.1 below;

Table 2.1: Infrastructure sector sub-categories

Economic infrastructure	**Social infrastructure**
Transportation (including toll roads, airports, seaport, and rail systems)	Education facilities
Utilities (including. water supply and sanitation, energy distribution networks, gas storage)	Health (health care facilities)
Communications (satellites, cellular towers)	Security – prisons, military stations
Renewable energy	Others - recreational parks, stadiums

Source: Deutsche Asset Management, March 2017

In general, it is likely that economic infrastructure generates more economic returns compared to social infrastructure (Oberholzer *et al.*, 2018). As can be seen from the table, infrastructure is very broad, diverse and heterogeneous, though the various types tend to share some common investments traits. Like most asset life cycles, infrastructure assets pass through four phases thereby generating different risk-return profiles at each stage. The four phases are namely;

Development infrastructure: this phase is characterized by a ‘high risk - high return’ maxim as it involves green field investment into the infrastructure sector (Oberholzer *et al.*, 2018).

Growth infrastructure: this stage is associated with growth and expansion, thereby exposing the firm to significant levels of market and operational uncertainties.

Mature infrastructure: the key features of this phase are steady, long-term, income-skewed returns, (as opposed to capital appreciation potential associated with the first two stages).

The last stage is the decline stage whereby the existence of the asset becomes questionable as new, smart and climate-friendly substitutes are introduced.

In further categorizing the infrastructure sector, some authors identify whether the investment is brown or green-field and whether the investment is in the operational or construction stage (Antropov & Perarnaud, 2013; Inderst & Stewart, 2014; OECD, 2015; Inderst, 2016). Greenfield investments involve the financing of a completely new infrastructure asset. This is very risky and huge amounts of capital expenditure (for extended periods) are required. Brownfield projects involve an investment into an already existing infrastructure asset which requires some extensions, refurbishments or repairs (Inderst, 2016). In this case the asset in question might be already generating some inflows.

2.2.2. Investing in the infrastructure sector- methods available

To participate in the infrastructure sector, investors can commit their funds (equity and debt) into the infrastructure sector using different methods. The options available when investing in infrastructure are obtainable in Table 2.2 below;

Table 2.2: Infrastructure investment routes

	Direct	**Indirect**
Unlisted	direct investment (private stock, project finance)	private and debt infrastructure funds
Listed	listed stocks, corporate and project bonds	listed equity and bond funds

Source: Inderst and Stewart (2014)

In the most basic form, investors can be involved in the primary and direct provision of the infrastructure product or service like power generation, water reticulation, and offer communication or satellite services (Inderst, 2013; Inderst & Stewart, 2014). This is capital intensive, long term in nature and likely to be risky in terms of development risk, construction risk and market risk. Direct investment in infrastructure enhances the provision of the base asset or commodity upon which other strategies of investing in infrastructure are 'derived' or based. Due to the capital intensive, illiquid and risky nature of primary direct investment in the infrastructure sector, only institutional investors (public and private), central governments and developmental banks have the capacity and expertise to use this route (Wold bank, 2018; CBRE Clarion Securities, 2019).

The indirect route is mostly pursued by investors who lack knowledge, experience, and are wary of the risk and complexities rampant in direct investment in infrastructure (Moss, 2014). Using the indirect option, investors can invest into investment companies specializing in funds committed to investing in infrastructure projects or shares. Theses investment companies and funds can be listed or unlisted (Kempler, 2016).

Through the unlisted direct route, where everything is done using private unlisted equity or debt, investors are exposed to the demerits of lack of transparency and illiquidity which might be (or might not be) compensated through illiquidity premiums (Inderst & Stewart, 2014). It is commonly claimed that this unlisted or private route provides room for portfolio diversification as the investments are not exposed to market euphoria and the irrational behavior of investors (Stack, 2014; Langley, 2016).

Investors can also opt for the listed option when investing in infrastructure. The merits of the listed option include informational transparency, liquidity, lower fees, small capital requirements, easy diversification and daily valuation (Julian & Humphreys, 2016). Listed shares are claims to the real assets owned by the issuer, thus the returns earned by stock investors are directly linked to the performance of the real asset in question, other things being equal. Valuation of unlisted investments is based on net tangible or underlying asset value. Listed infrastructure offers potential diversification benefits and stable cash-flows (RARE, 2017; Geysen, 2018).

Rational economic propositions suggest that investors are indifferent when it comes to choosing between listed and unlisted assets as the fundamentals are actually the same (Moss, 2014). As put forward by Kempler (2016), listed and unlisted infrastructure investments are homogenous as they are based on the same assets, regulated by the same institutions, and management and corporate governance issues are similar.

However, differences might be noticeable in the pricing, fees, correlations, liquidity, opportunity set, portfolio rebalancing requirements and the sources of returns and risk (Stack, 2014). Due to these noticeable differences, listed and unlisted assets have a tendency to complement each other over short periods, as they have weighty differences regarding their correlations, volatility, and liquidity and return levels (Julian & Humphreys, 2016, Howard, 2019). As such, investors tend to derive diversification benefits if listed and unlisted assets are part of the same portfolio (Moss, 2014). As we increase the investment horizon to long term, these features tend to converge, making listed and unlisted infrastructure assets close substitutes, providing room for investors to swap listed for unlisted infrastructure investment (De Bever *et al.*, 2015; Moss, 2014).

As is evident from this outline, investing in infrastructure is actually based on the tangible or real asset and all other options are simply ‘derivatives’. It is possible that the performance and risk of the discussed options can be significantly different, though they are all based on the same foundation, the real asset. This study exposed the similarities and differences between the stochastic distribution, the risk-adjusted return profiles and the correlational features of listed and unlisted infrastructure investments. Such an expose makes significant contributions to the role played by infrastructure investment in emerging markets when it comes to asset allocation, portfolio construction and portfolio rebalancing (Bourgi, 2018).

2.2.3. The infrastructure gap estimates

The need for infrastructure is increasing in both developed and developing economies due to urbanization, aging infrastructure, an expanding middle class, economic growth, smart technology and the go-green movement (Oberholzer *et al.,* 2018). Although the lack of infrastructure is a global challenge, the infrastructure gap in emerging markets is particularly huge. This is due to long periods of underinvestment, economic growth and burgeoning populations (Willsher, 2018).

Quantifying physical infrastructure needs is a very difficult task, and the same holds when determining the infrastructure gap in monetary terms (Geysen, 2018). Inderst & Stewart (2014) noted that approximately US$ 80 trillion is needed cumulatively and globally by 2030 for new infrastructure in all sectors (including the harnessing of smart technology). This amount, however, excludes the funds needed for maintenance purposes. Emerging economies require 60% of global infrastructure needs (Blanc-Brude, 2018). As stipulated by the World Economic Forum (2013) and Authers (2015), the global infrastructure financing gap is estimated to be about US$ 1 trillion per annum, excluding investments needed to adapt to climatic changes and green technologies. If such extra investments are included alongside the United Nations Development goals, the gap would rise to between USD 3.3 and USD 5 trillion per annum (Woetzel, Garemo, Mischke, Hjerpe, & Palter 2016). This clearly testifies to the failure of traditional providers and owners of infrastructure assets to catch up with demand. The lack of infrastructure the world over is now expectedly a risk to global economic growth and prosperity (Nietvelt, 2019).

Inderst (2013) and Bhattacharya, Romani, and Stern (2012) found that 32 Asian emerging economies required infrastructure assets amounting to USD 8.2 trillion for the period 2011 to 2020. Oberholzer *et al.*, (2018), approximated the infrastructure deficit in Africa to be around USD 130 billion annually. Such a gap in Africa is likely to be understated given the level of data unavailability in the continent. These phenomenal infrastructure gaps result in overcrowded roadways, inadequate affordable housing, and erratic power supplies, even in the land of greener pastures. As noted by Furnes, (2019), even in developed nations like the USA, there is an infrastructure gap and approximately an extra USD 150 billion is required annually to meets its infrastructure needs. The existence of a huge infrastructure gap suggests the existence of an unlimited supply of infrastructure investment projects in both developing and developed economies (CBRE Clarion Securities, 2019).

As a way of luring institutional investors into the infrastructure sector, Scoville, Ligere & Lyon (2015) noted that the European Commission made some amendments to the Solvency II regulations, reducing the capital charges applicable to infrastructure investments, as the Solvency II European Union directive used to penalize long maturities (Courtois, 2013). The launch of the Africa 50 Infrastructure Fund Initiative aimed at mobilizing resources for infrastructure in Africa, is another example of efforts made to reduce the infrastructure gap (Wentworth & Makokera, 2015). This indicates the growing urgency to address new and deferred infrastructure needs as governments are under immense pressure to deleverage their statement of financial positions (balance sheets) and reduce debt (Hussain *et al.*, 2019).

The introduction of partnerships and banks like the Asian Infrastructure Bank (AIB) and BRICS' (Brazil, Russia, India, China and South Africa) New Development Bank (NDB), are some of the milestone projects launched in attempt to reduce the infrastructure financing gap. The same can be said of the establishment of the partnership between the National Association of Securities Professionals (NASP) and the United States Agency for International Development (USAID), known as Mobilizing Institutional Investors to Develop Africa's Infrastructure (MiDA), launched in 2016, and the launch of the Emerging Africa Infrastructure Fund (Saha & Messervy, 2018; Willsher, 2018).

All these initiatives and partnerships evidence the existence of the infrastructure gap which can be utilized by institutional investors, other things being equal. Besides the potential for economic returns, there is a strong and compelling social case for investing in infrastructure (Antropov & Perarnaud, 2013). Adequate infrastructure enhances adequate provision of health amenities, improves the standard of living, spurs economic growth, drives human capital development, reduces the cost of doing business, and enhances trade among nations (OECD, 2015; World Bank, 2018a). Restated, investment in infrastructure is treated as a social responsibility gesture by the populace, which in turn amplifies the corporate image of the investor involved.

2.2.4 Institutional investors and assets under their management

Institutional investors as defined above enjoy sizable economies of scale as they possess a strong capital base, unmatched expertise and knowledge (Gatti, 2019). As indicated by UNTT, (2015) forum, institutional investors can commit up-to 60% of their assets into illiquid, long duration investments. Three common types of institutional investors are briefly outlined hereunder:

Pension funds - these firms receive contributions from the working class and make investments according to their investment policies (Blanc-Brude, 2018). They will start to make payouts when the contributor reaches retirement age, normally after 25 to 40 years. These can be public or private institutions set up for the sole purpose of providing earnings to pensioners (Oberholzer *et al.*, 2018). For example, pension funds receive contributions when an individual enters the workforce; they may only start paying benefits 25 to 35 years later, and continue paying out the benefit amount for 15 – 30 years. As such, institutional investors possess a pool of 'patient' capital (from premiums or contributions) which can be invested over long periods.

Life insurance companies- these firms collect premiums or contributions from members and make investments using pooled funds; they make payouts upon the death of the member (Gatti, 2019).

This creates a good source for a long term source of capital, concomitant with green-field infrastructure investments.

Sovereign Wealth Funds - (SWF) these institutions are designed by central governments as special-purpose investment schemes or provisions. The main aim of such funds is the preservation of the nation's resources for future generations and ensuring macro-economic stabilization (OECD, 2015).

In terms of assets under their management and financial capacity, institutional investors possess tremendous and strong financial muscle. At global level, Fages *et al.,* (2018) estimate the assets under management to be approximately US$80 trillion. Considering only pension funds, assets within their jurisdiction in emerging and developing markets amounted to US$ 2.5 trillion as of 2012. On the same note, Mcgroarty (2015) noted that pension funds command an asset holding amounting to approximately US$370 billion in Africa. In 2016, the total assets under African sovereign wealth funds' management were approximately $157 billion, whereas South African retirement funds were worth USD318 billion in 2017 (Oberholzer *et al.,* 2018). Bernhardt and Messervy, (2018) approximated that the assets under the management of OECD institutional investors amounts to $55 trillion. Illustratively, less than a quarter of a percent of total OECD institutional investors' assets are enough to fulfill Africa's infrastructure needs and sustainable developmental goals for energy, water, and sanitation, specifically (Bernhardt & Messervy, 2018). This nails home the point that, capital is available, and investment options for this capital, are available and even increasing. However, empirical evidence is needed in order to prove whether the 'fertile ground and promising investment habitat' really provide tangible intrinsic investment features as per institutional investors' expectations.

2.2.5. Linking infrastructure investments and institutional investors

This section provides a loop between infrastructure investment features and institutional investors' expectations in emerging markets. The section unveils the existing natural fit between what can be offered by the infrastructure sector and what institutional investors are looking for in their attempt to meet their investment goals.

2.2.5.1 Investment features of infrastructure investments

The infrastructure sector provides products and services required on a day to day basis like water, transportation, education, medical care facilities and energy, thereby commanding a diversified captive customer base (Ligere & Lyon, 2015). This makes infrastructure a pre-requisite for sustained economic growth and an enhanced standard of living. Infrastructure investments theoretically and fundamentally, offer investment features that can be of value and attractive to institutional investors. Such investment attributes include;

Huge initial capital outlay

Greenfield infrastructure investments often require a huge initial capital outlay. These outflows and subsequent capital expenditure demands, can take years before the project starts generating any return (UNTT, 2015; Levy, 2017). As such, institutional investors with a huge and strong ‘patient capital’ base (capital investable for long periods before any return is demanded), are well suited for such investments (Blanc-Brude, 2018).

Long economic life

Infrastructure assets are long term in nature (both the economic and technical lives), stretching for decades with low cost maintenance requirements (Thompson, 2019). Take for example schools, roads and airports. These can exist for decades with minimal maintenance costs (CBRE Clarion Securities, 2019). Consequently, infrastructure assets possess the ability to generate revenues for long periods in tandem with their economic and technical lives (Riding & Emma, 2019). This is in tandem with the long run annuity type of liabilities in organizational investors’ books of accounts.

Less sensitive to economic and business cycles

The demand for infrastructure services tends to be inelastic and less sensitive to economic cycles, as infrastructure products and services are required, regardless of the industrial and economic cycles (Levy, 2017). This is due to the fact that substitutes hardly exist in the infrastructure market. This defensive feature is amplified by the existence of high barriers to entry (huge initial capital outlay), and the oligopolistic and monopolistic characteristic of the infrastructure sector (Chhabria *et al.,* 2015; Gatti 2019, Howard, 2019). As argued by Kempler (2016), some infrastructure assets’ returns concessions are set, with limited or no link to cyclical demand or volumes.

Predictable, steady and long term revenues

Due to less sensitivity to economic and business cycles and the monopolistic nature of the infrastructure sector, cash-flows from the sector are relatively stable, non-cyclical and predictable, theoretically (Anagnos, 2016). This investment feature enables the infrastructure sector to offer above average returns, and superior dividend payout ratios, relative to other asset classes like real estate (Thompson, 2019). For example, for the past 20 years, listed infrastructure earned 3% and 4% above global stock and global bonds respectively (CBRE Clarion Securities, 2019). On the same note, contracts, concessions and agreements in the provision of infrastructure services are long term in nature, which enhances the generation of stable, predictable and sustainable cash inflows (Geysen, 2018).

Inflation hedging capability

Most infrastructure concessions and agreements provide a clause allowing firms to adjust their products and services prices in line with inflation rates (Turner, 2016; Baginski 2019). On the same note, regulated infrastructure assets are provided with return formulae that enable the asset to earn specific target return regardless of economic conditions (Chhabria *et al.*, 2015; Kempler, 2016;World Bank, 2018b). This promotes the steadiness and predictability of infrastructure returns as highlighted above. As noted by KPMG, (2017) and CBRE Clarion Securities, (2019), returns for regulated utilities (set by regulatory authorities) in the United Kingdom and Italy are set based on real returns, thereby allowing a direct link to inflation. This investment feature of the infrastructure sector is a hallmark, given that unexpected inflationary upswings are corrosive and costly to long term investors (Bahceci & Leh 2017). It is claimed that 85% of listed infrastructure investments can pass-through inflation shocks in developed markets, thereby generating inflation hedged revenue (CBRE Clarion Securities, 2019). It remains to be known as to whether the same claim holds water in emerging markets.

Notable diversification ability

Infrastructure assets offer low sensitivity and correlation with economic cycles and other assets, at least theoretically (Inderst, 2013; Blanc-Brude, 2015). On the same note, Weiner (2014) and Deutsche Asset Management (2017) are of the opinion that infrastructure assets are not highly correlated with bonds and equity, thereby providing diversification benefits to portfolio holders. The defensive traits of the infrastructure sector already highlighted above enables it to play a strategic role in portfolio risk diversification (O'brien & Leung, 2018; Baginski, 2019)

Less volatile returns and cash-flows

Blanc-Brude (2018) as supported by Bigman and King, (2016) and Geysen, (2018) purports that infrastructure investment returns and revenues are less volatile compared to equivalent sectors and capital markets as their demand and revenues tend to be inelastic or less responsive to economic down turns. The same sentiments were echoed by CBRE Clarion securities (2019) looking at global listed infrastructure. Deutsche Asset Management (2017), and Turner, (2016) cite less volatility as one of the key investment attractions of the infrastructure sector.

In summary, it is largely believed among investment analysts and industrialists that the infrastructure sector is lowly correlated with other asset classes, improves risk-return profile, and offers long term, stable, inflation-linked and reliable cash inflows and returns (Moss, 2014; Oyedele, 2015; Scoville, *et al.*, 2015; Bigman & King, 2016; Kempler, 2016; O'Brien and Leung, 2018; CBRE Clarion Securities, 2019; Nuveen Asset Management, 2019; Thompson, 2019). On the same note, (Baginski 2019,) and Bahceci and Leh (2017) indicated that infrastructure sector investments afford investors risk neutralization merits; inflation shield and better income tied with stable cash inflows. Subsequently, inclusion of infrastructure investments in a portfolio is expected to theoretically bring with it such positive strategic and attractive investment attributes. The resultant portfolio is expected to be less volatile, diversified and efficient, with inflation linked returns. In the same train of thought, Weiner (2014), Norges Bank (2015), and Blanc-Brude (2016) opine that infrastructure investment in emerging markets is a sure way of realizing a well-diversified portfolio. In possessing all these too-good-to-be-true salivating investment features, no rational economic investor is expected to ignore infrastructure investments, other things being equal.

However, as argued by Rodel and Rothballer (2012) and Bird *et al.,* (2014), these investment characteristics of infrastructure assets are challengeable as the infrastructure market matures and given the deregulation drive in most economies. Superior returns are often expected from infrastructure assets with high pricing power, besides the obvious inelastic demand (Gatti 2019; Wurstbauer and Schafers 2015). It is a known fact that deregulation in the infrastructure sector, might render this investment feature extinct (Gatti, 2019). On the same note, Blanc-Brude (2019) and Lauridsen *et al.*, (2018) opine that the pronounced investment features of infrastructure assets in developed and mature markets are likely to be different from features obtaining in emerging economies. Relatedly, infrastructure investments market is not easily accessible to the general public and is laden with information asymmetry, political risk and insufficient capacity of government to work with institutional investors in emerging nations (World Bank, 2018b). This indicates the need for deeper evaluation of emerging markets where the infrastructure market is still at infancy stage, so that coherent conclusions can be drawn from the subject matter.

2.2.5.2 Institutional investor needs and their hunt for new assets.

Traditionally, institutional investors held public equity, and government bonds as their core assets (Bolton Consultation Group 2017; Manning, 2019). In normal and efficient capital markets, such a portfolio earned them the returns required to meet the objectives of institutional investors profitably. Unfortunately, capital markets are not always efficient, static and rational. As commented by KPMG (2017), investors need to constantly check on their investment strategies for survival, especially during and after violent market swings such as the 'dot com bubble' of 2000 (whereby the NASDAQ Composite Index fell by 80%).

Recent violent market swings triggering portfolio revision include the global financial crisis of 2007/8 (where the S&P 500 Index declined by 56%), the European debt crisis of 2009 and China's significant market downturn of January 2016 where benchmark indexes lost 12 Trillion Yuan (Kempler, 2016). Such market shocks, coupled with the Brexit referendum of 2016, resulted in global major stock indices shedding points. For example, during the Brexit referendum of 2016, Germany's DAX shrunk by 8.6%, London's FTSE100 was down by 6% and the S&P500 fell over 8% adding volatility to the already fragile and feeble global economy (Daniel, 2016; Kempler, 2016). These market shocks were punctuated by depressed stock market returns, new regulatory frameworks, (such as Basel III and

Solvency 11) and falling interest rates, which adversely affected the performance of many institutional investors, thereby creating funding gaps (McConville, 2019). The recent protectionist approach by the USA, evidenced in trade wars with China, worsened the situation (Nietvelt, 2019).

As such, it is now public information that the glory and attractiveness of general stocks and bonds is steadily becoming extinct (Manning, 2019). Restated, traditional asset allocation is failing to meet the long tenure objectives of organizational investors like portfolio diversification and long-tenure inflation hedged returns. The above mentioned financial market swings and experiences coupled with compelling demographic trends, and characterized by ageing demographics and lower retirement savings, significantly altered institutional investors' perceptions towards their traditional asset allocation strategy, with their focus and interest now targeted towards emerging markets and new asset classes (Bahceci & Leh, 2017; Kovarsky, 2018, World Bank, 2018b).

In an attempt to avoid poor returns, institutional investors are now in a new drive to diversify their portfolios and supplement their core assets (De Laguiche & Taze-Bernard, 2014; KPMG, 2017). Concurring with this claim, Kovarsky, (2018) commented that post the 2007/8 crisis period, institutional investors' search for yield, diversification, and defensive alternative assets gained momentum. The compelling aim of these investors is to avoid poor real returns, and reduce portfolio volatility on a long term basis (De Laguiche & Taze-Bernard, 2014; Gatzert & Kosub, 2014; KPMG, 2016).

Institutional investors are hunting for liability-matching, less complex and tangible assets which provide new and better sources of long-tailed stable investments, predictable rewards, and comprehensive risk reduction merits (Imrie & Fairbairn, 2014; Riding & Emma, 2019). Put differently, institutional investors seek to match their long tailed portfolio liabilities (annuity-type liabilities,) to long-tailed stable, sustainable and predictable returns when making investments (Kempler, 2016; Weber Staub-bisang, & Alfan, 2016; Baginski 2019).

In a nut shell, institutional investors are in search for:

- Long term steady inflation hedged returns
- Sustainable and predictable returns
- Smoothing risk or volatility
- Capital preservation and
- Diversified portfolio

From the above outline, it is self-explanatory that what the infrastructure sector offers (investment features) is actually what institutional investors are in search of, at least theoretically (Subhanij, 2017). As alluded to earlier on, the investment features of the infrastructure sector are not homogenous across the globe. This drives home the need to empirically evaluate the ability of infrastructure investments to meet such institutional investor expectations in emerging markets where the infrastructure market is still developing.

2.2.6 Closing the loop

Institutional investors' search for investment avenues in the face of market downturns seem to have been answered, at least theoretically. Infrastructure sector investments seem to be the appropriate investment niche for institutional investors saddled with performance seeking (high Sharpe ratio) and liability hedging goals. Over and above meeting investment goals, institutional investors derive reputational and social benefits from investing in infrastructure assets which are essentials for economic development and the social upward mobility of the inhabitants. The infrastructure gap, which can be utilized by institutional investors, is ever widening. Institutional investors possess significant 'patient' capital which can be devoted to long term infrastructure investments. This nails home the claim that the partnership or marriage between institutional investors and infrastructure sector is natural, other things being equal. What remains unknown is whether the claimed investment features of the infrastructure sector exist in developing economies.

2.3. An overview of the conceptual framework for the study

As decried by Wurstbauer and Schafers (2015), lack of theories on infrastructure investments boggles the mind of an average academician, given the economic importance of infrastructure assets in an economy. As such, this section outlines the conceptual framework for the study. The section gives a recap of the main concepts (infrastructure investment features and institutional investor needs) under study, addressing how they are linked and highlighting the main thrust of the study.

Infrastructure investments theoretically (narratively), offer some features that can be of value to institutional investors. Such features include; above average dividend payout ratio, long-term stable and predictable revenue streams, and low correlations with other asset classes (Oyedele, 2015; Scoville, *et al.*, 2015; Burke, 2017; Thompson, 2019). Adding on to this, Inderst, 2013; Moss, (2014); Blanc-Brude, 2015; McConville; 2019) identified such intrinsic characteristics to include: oligopolistic characteristics, inflexible demand, foreseeable and steady cash inflows, high profit percentages, and long economic and technical tenor. Chhabria *et al.*, (2015) opines that prices for services rendered by infrastructure firms tend to be indexed to economic rates such as inflation. Such salivating narrative financial intrinsic features are worth studying as they might not be reflected in returns commanded by the infrastructure sector.

Institutional investors like pension funds are the owners of long period ‘patient’ capital which can be committed to long term investments (Eurasian Business Coalition, 2015; UNTT, 2015; Wurstbauer & Schafers, 2015). Institutional investors seek to match their long tailed portfolio liabilities (annuity-type liabilities,) to long-tailed stable and predictable returns when making investments (Weber *et al.,* 2016). Some of the key needs of institutional investors, as claimed by Kempler (2016), Imrie and Fairbairn (2014) and World Bank, (2018b) include; maximizing returns/income, smoothing risk or volatility, capital preservation, diversified portfolio and generating inflation protected returns.

Traditionally, institutional investors hold mainly public equity and bonds as their assets in an attempt to realize their goals (Bolton Consultation Group, 2017). Under normal and efficient capital markets, such a strategy gives them the normal returns they require to meet their objectives. Unfortunately, capital markets are not always efficient, static and rational. As such, institutional investors are in constant search for new investment avenues to meet their objectives (Hussain *et al.*, 2019).

From the above narrative, it is self-evident that what infrastructure investments can offer (theoretically) is what institutional investors are seeking. As such, it is expected that a significant size of an institutional investor’s portfolio comprises infrastructure investment. Interestingly, this is not evident, especially in emerging economies saddled with a mammoth infrastructure gap and increasing (which infrastructure investors can utilize). Institutional investors the world over, save for Australia, UK, Canada and USA, seem to be taking a starring role by investing roughly 1-3% of their total assets in infrastructure (Caliari, 2015; Oberholzer *et al.,* 2018). This drives home the need to evaluate the ability of infrastructure investments to meet institutional investor expectations. It is a plausible possibility that these salivating features only exist in theory. On the same not, accessing the infrastructure market is laden with challenges and risks (UNTT, 2015). Such challenges include; high operational costs, waek governance, settlement and operational risks which are more pronounced in emerging markets compared to their developed counterparties.

In evaluating the ability of infrastructure investments to meet expectations of institutional investors, this study follows the process presented in Figure 1 below.

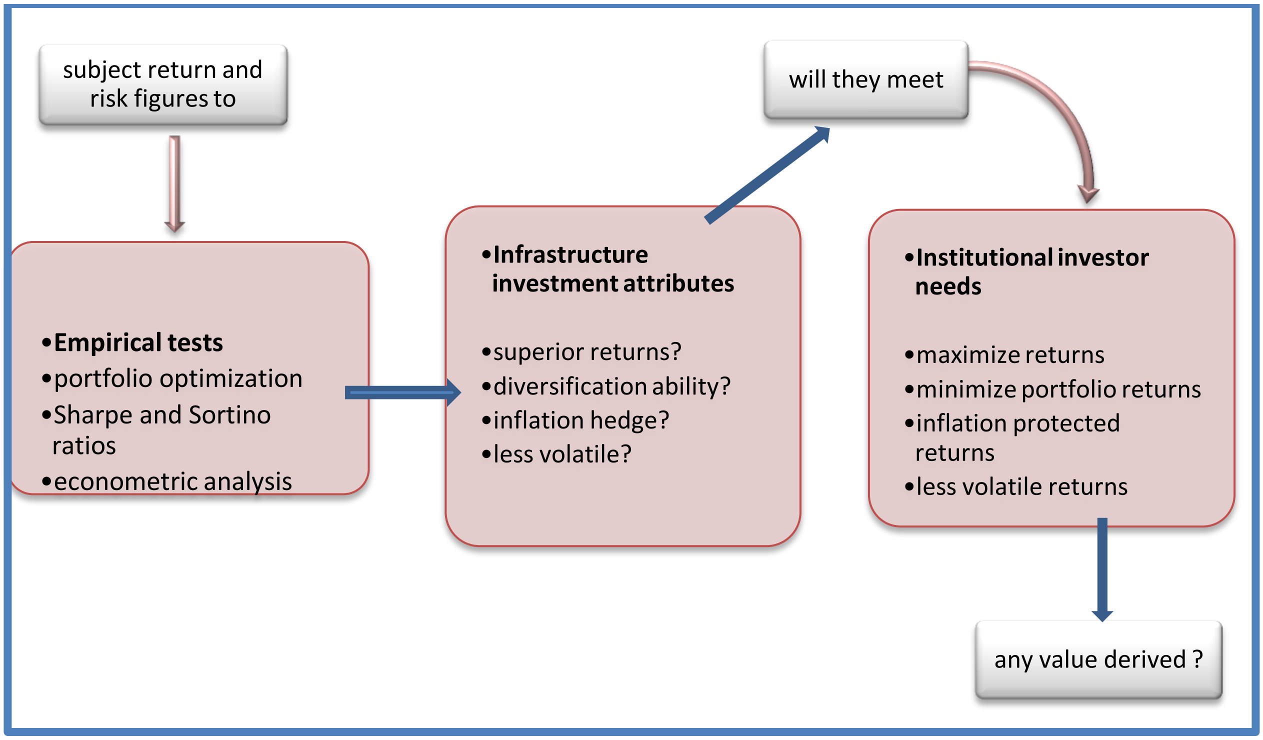

Figure 2.1: Conceptual framework diagrammatized.

This study used return and risk data from infrastructure investments in emerging markets and subjects these figures to econometric tests, risk-adjusted return measures and a portfolio optimization process. This enabled us to ascertain the ability of empirical data from infrastructure investments to concur with narratives claimed about the same. The ability or inability of data to concur with the claimed financial features of infrastructure investments answers the question on what value can institutional investors derive from infrastructure investments in emerging markets in their quest to achieve their objectives. It is possible that infrastructure investment data might concur with some narratives but fail to satisfy some claims.

2.4. Empirical literature review

As already alluded to earlier on, empirical literature on the subject under study is scant; as such the available academic studies are detailed in respective papers.

2.5. Chapter summary

This chapter detailed the investment features of the infrastructure sector in comparison to what institutional investors are in search of. The natural fit was established, indicating the ability of the infrastructure sector to generate inflation linked long term returns which can be matched to the long term inflation-linked liabilities of institutional investors. The existing infrastructure gap to the tune of trillions USD annually, was established in this section. The infrastructure gap presents fertile ground which can be utilized by well-resourced institutional investors in possession of 'patient' capital. The doubts cast on the empirical existence of salivating investment narratives about the infrastructure sector, was also established, indicating the possibility of heterogeneous investment features in developed and developing economies. How the concepts are connected and the way the study evaluated infrastructure investment features, was articulated in the last section of this chapter. The forthcoming chapter addresses the ability of the infrastructure sector to generate superior risk-adjusted returns and diversify portfolio risk in emerging markets.

CHAPTER 3

THE ROLE OF INFRASTRUCTURE INVESTMENTS IN A RISKY PORTFOLIO IN DEVELOPING ECONOMIES

3.0. Chapter introduction

This paper examined the potential role which can be played by infrastructure sector investments in emerging markets in a risky portfolio. The paper specifically evaluated the ability of infrastructure to amplify portfolio returns and dampen portfolio risk. This is against the claim that infrastructure investment attributes derived from inelastic demand and captive customer base enable infrastructure to earn super returns and reduce portfolio risk. The ability of infrastructure investment to exhibit these investment attributes will sweeten the attractiveness of infrastructure in emerging markets. In other words, this paper gives evidence on what institutional investors can get by investing in infrastructure in emerging markets in their hunt for alternative assets which generate superior returns and reduce portfolio risk.

Status of the paper- the paper went through preliminary desktop review and now waiting for proper review from the Indian Journal of Finance.

Abstract

The paper investigates the benefits of adding infrastructure investments to a risky portfolio made up of listed real estate and listed general equity in emerging economies. The study used correlation analysis, portfolio optimization, Sortino ratio and the Sharpe ratio to evaluate the value of infrastructure investments in an optimal risky portfolio. It found that investment in private or unlisted infrastructure enhances optimal portfolio return and reduces portfolio risk. This indicates unlisted infrastructure investment's capacity to effectively reduce portfolio risk and amplify portfolio returns, implying investors can meet their 'performance seeking' objective by including such infrastructure in a risky portfolio. Interestingly, the opposite was found to be true for listed infrastructure, implying that listed and unlisted infrastructure investments complement rather substitute for each other. It is thus recommended that investors should consider the heterogeneous nature of infrastructure investments when making asset allocation decisions.

3.1. Paper introduction

Portfolio management is an on-going process that includes scouting for new investment avenues and committing resources to same to earn substantial returns. Investors all over the world are in search of new investment avenues as the financial and property markets are characterized by very low returns, low interest rate episodes, economic uncertainty and wild market swings (Oyedele, Adair, & McGreal, 2014; Kovarsky, 2018; Thompson, 2019). Institutional investors with short- and long-term liabilities constantly seek new investment routes in an effort to reduce risk without sacrificing returns (Moss, 2014; Korvasky, 2018). Among other objectives, they hunt for investments that provide the risk reduction merits, purchasing power preservation and improved yields (Bahceci and Leh, 2017; Blanc-Brude 2018; Korvasky 2018).

Institutional investors have access to 'patient capital' which can be invested for medium to long terms in tandem with their liabilities. Theoretically, their goals can be met by means of investments in infrastructure which are generally long term in nature, have monopolistic/oligopolistic strategic powers and produce steady inflation protected cash inflows (Blanc-Brude, 2018; Kovarsky, 2018). Infrastructure could thus be the new investment niche if the sector lives up to claimed financial or economic attributes like risk diversification and generating superior returns. Thus, all other factors held constant, institutional investors are expected to allocate substantial portions of their investments to the infrastructure sector.

The asset allocation decision should be treated with caution as it determines more than 80% of a portfolio's return and risk (Moss, 2014). As such, there is need to empirically evaluate infrastructure investments' financial attributes so as to ascertain whether institutional investors can derive significant benefits from investing in this sector. These attributes include risk diversification ability, return enhancement, inflation hedging ability and volatility reduction (O'Brien and Leung, 2018). Such evaluation is key in developing nations where there is a dire need for infrastructure due to decades of underinvestment, urbanization, industrialization and population growth as well as climate change and the 'green technology movement' (Woetzel, *et al.,* 2016). The evaluation will determine whether infrastructure investment can be treated as a new investment 'habitat' for institutional investors in emerging markets (Wurstbauer & Schäfers, 2015).

The infrastructure gap in emerging markets amounts to USD 1.3 trillion per annum to merely keep up with normal economic and demographic growth (World Bank, 2018a). This gap increases three to five fold if green technology, the United Nations' developmental goals and adaptation to climate change are taken into consideration (Authers, 2015; Woetzel *et al.,* 2016; World Bank, 2018a). When replacement costs are included, the infrastructure gap increases exponentially (given the destructive conflict in emerging nations- like wars, acts of terrorism). It presents fertile ground that can be utilized by both domestic and foreign institutional investors. However, take up of infrastructure assets in developing economies by corporate investors will only be attractive if such investments can live up to claimed financial and economic attributes, other things being equal.

This empirical research evaluated the portfolio return enhancement and risk diversification benefits of adding infrastructure investments to a risky portfolio in emerging markets. This was achieved by comparing the risk-adjusted return of an optimal risky portfolio comprised of traditional assets (real estate and common stock) against an optimal portfolio made up of traditional assets plus infrastructure (real estate, common stock and infrastructure investments).

The objective of portfolio diversification is to realize optimal returns at any given level of risk (the free lunch in financial markets). Diversification aims to reduce specific or unsystematic risk without sacrificing returns (Kempler, 2016). Unsystematic risk is specific to a particular industry, country, sector, or economic or geographical zone. The investor needs to choose assets whose returns are minimally correlated to achieve a well-diversified portfolio. The combined effects of globalization, advances in information technology, significant capital market integration, and diversification might cast doubt on infrastructure assets' ability to achieve this objective; hence the need for empirical analysis.

3.1.2. Overview of infrastructure investments

Infrastructure is easier to identify than define (Gatzert & Kosub 2014). The online American Heritage Dictionary (2016) expresses it as:

"The basic facilities, services, and installations needed for the functioning of a community or society, such as transportation and communications systems, water and power lines, and public institutions including schools, post offices, and prisons."

In general, infrastructure investments are classified into two classes, namely, economic (transport, utilities, communication, energy) and social infrastructure (education, health, recreation) (Wurstbauer & Schafers, 2015; Inderst, 2016).

Investment in infrastructure is never lost as it results in improved standards of living, increased life expectancy, poverty alleviation, national competitiveness and efficient use of physical assets, other things being equal (Courtois, 2013). The options available when investing in the infrastructure sector can be generalized as direct or indirect using listed or unlisted options. Direct investment occurs when an investor commits resources to the primary provision of infrastructure products and services. This can be done using either private equity (unlisted) or by purchasing shares (listed) of a company involved in the primary provision of infrastructure products. The other option is the indirect route, whereby the investor commits resources to funds and collective investment schemes (listed and unlisted) that specialize in infrastructure investments. Rail Mass Transit growth infrastructure fund in Thailand and the Isibaya fund in South Africa are examples of these funds (Subhanij, 2017)

As noted by Anagnos (2016), economic propositions suggest that investors are indifferent when it comes to choosing between listed and unlisted assets as the fundamentals are the same. However, there are discernable differences in the pricing, correlations, liquidity and sources of returns and risk (Moss, 2014). Listed and unlisted assets tend to be complementary on short term basis, as they display substantial differences in their correlations, volatility, and liquidity and return levels. This implies that investors can benefit from including both listed and unlisted assets in their portfolios (Moss, 2014; Anagnos, 2016). As the investment horizon increases to the long term, these features tend to converge, rendering listed and unlisted infrastructure assets close substitutes and providing room for investors to swap listed for unlisted infrastructure investment (De Bever *et al.*, 2015). As such, this paper examines whether listed infrastructure complements or closely substitutes for unlisted infrastructure investments in emerging markets where the infrastructure market is still in its infancy.

3.1.3. Infrastructure investment features and institutional investors' needs

Investment analysts and scholars generally believe that infrastructure investments are minimally correlated with other asset classes, and that they improve the risk-return profile, as well as offer long-term stable and reliable cash inflows and returns (Moss, 2014; Scoville *et al.*, 2015; Oyedele, 2015; Nuveen Asset Management, 2019; Thompson, 2019). Thus, including infrastructure investments in a portfolio is theoretically expected to yield significant benefits (O'Brien & Leung, 2018). The resultant portfolio is expected to be less volatile, and more diversified and efficient with inflation linked returns. Weiner (2014), Norges Bank (2015), and Blanc-Brude (2016) are of the opinion that infrastructure investment in emerging markets is a sure way of achieving a well-diversified portfolio. However, as Rodel & Rothballer (2012) and Bird, Liem & Thorp (2014) argue, these intrinsic characteristics of infrastructure assets (such as duration hedging, and low correlations with other markets) are open to debate.

Burke, (2017) and Kovarsky (2018) commented that post the 2007/8 crisis (punctuated by low growth, and low interest rates), investors' pursuit of yield, diversification, and defensive alternative assets gained momentum. Bahceci & Leh (2017) note that infrastructure investments provide investors with the portfolio risk reduction, inflation shield and improved return coupled with stable cash inflows. In an attempt to avoid poor returns, and reduce portfolio volatility, institutional investors are now seeking to diversify and supplement core assets on a long-term basis (De Laguiche & Taze-Bernard, 2014; Gatzert & Kosub, 2014; Kempler, 2016; KPMG, 2016; Kovarsky, 2018). They are thus keen to identify liability-matching, less complex and tangible assets which provide new and better sources of long-tailed stable, predictable and risk-attuned yields, on top of comprehensive risk reduction advantages (Imrie & Fairbairn, 2014; Kempler, 2016; Weber, *et al.*, 2016). Infrastructure investments are a natural fit for institutional investors pursuing healthy returns and liability hedging, among other objectives (Levy, 2017; Blanc-Brude, 2018). This highlights the need to empirically evaluate infrastructure investments' ability to meet such expectations in emerging markets.

3.1.4. The infrastructure gap in emerging markets

Kovarsky (2018) and the International Finance Corporation (2017) note that demand for infrastructure exceeds supply in many countries as governments confront fiscal pressure and are looking to reduce rather than expand their balance sheets. The situation is acute in emerging economies where the infrastructure market is still developing, and national governments are already saddled with financial, economic, social and political obligations. The World Bank (2018a) estimates that a USD 1.3 trillion annual investment is required to just keep up with normal economic and demographic growth in emerging nations. Adjusting for green infrastructure, climate change and the United Nations Development goals, the gap would rise to between USD 3.3 and USD 5 trillion per annum (Woetzel *et al.*, 2016; World Bank, 2018a). In Africa, the infrastructure gap is to the tune of USD 130 billion annually (Oberholzer *et al.*, 2018). A lack of quality infrastructure undermines economic growth prospects as well as the possibility of migrating to new and smart technology. The infrastructure gap thus offers a fertile investment ground where institutional investors can provide investment and achieve their personal objectives.

This research paper is prepared in the following manner: the subsequent unit gives snapshots of empirical studies regarding the ability of infrastructure investments to enhance portfolio performance and reduce portfolio risk. The third unit converses the methodology adopted in conducting the investigation on the role of infrastructure investments in a risky portfolio in emerging markets. The fourth segment outlines the study's findings, and the final part of the study affords overall conclusions and recommendations to different stakeholders.

3.2. Literature review

There is a scarcity of empirical examination on infrastructure investment, which could be partly attributed to the unavailability of data even in developed nations, until recently (Wurstbauer & Schafers, 2015). The shocks experienced in the credit and property marketplace in the course of the world-wide financial crisis of 2007/8 prompted investors to tap into infrastructure investments, sparking academic interest in this phenomenon (Thierie & De Moor, 2016).

At the global level, Chhabria, *et al.*, (2015) found that the FTSE Global Core Infrastructure Index outclassed USA stocks, international common stocks and world-wide bonds from its launch in 2005 and did so with lower volatility. Kempler (2016) and Moss (2014) concluded that global infrastructure performed better than global equities and global bonds. De Bever *et al.* (2015) showed that global infrastructure earned high returns from 2003 to 2015, while Daniel's (2016) examination of US data found that infrastructure provided better returns and enhanced portfolio returns compared to other asset classes. However, the sector's ability to provide superior returns might decline as the industry matures and deregulation occurs (Wurstbauer & Schafers, 2015). Panayiotou & Medda (2014), who used infrastructure indexes in the UK and Europe from 2000 to 2014, and Oyedele (2015) noted that infrastructure assets outperformed traditional assets and provide better portfolio returns if combined with traditional assets although the level of risk was not reduced. Thus, infrastructure investments are performance enhancers rather than risk diversifiers.

Finkenzeller (2012) noted that investors that committed resources to infrastructure development in Australia enjoyed increased returns, but diversification was limited. Investment in infrastructure in the US offered better returns and enhanced diversification as such investments were less affected by the economic crisis than asset classes like real estate and common equity (Panayiotou & Medda, 2014). On the same note, Newell, *et al.*, (2011) noted that only unlisted infrastructure investment earned better returns in Australia when adjusted for risk, and provided significant portfolio diversification. Oyedele (2015) analyzed the UK market from 2001 to 2010 and concluded that investment in infrastructure offers portfolio diversification benefits due to the fact that it is minimally linked with standard or traditional asset categories. Bahceci and Weisdorf (2014) examined infrastructure investment cash flows from US and Western Europe and noted the existence of diversification opportunities across infrastructure subsectors and geographical areas. This suggests that infrastructure investments diversify specific risk.

Most of the reviewed studies used bivariate correlation as a measure of diversification ability in the developed world. The study on which this paper is based went a step further and employed the portfolio optimization method, Sharpe ratio and Sortino ratio in comparing the risk-return profiles of optimal portfolios with and without infrastructure investments in emerging markets. It thus contributes to the debate on whether or not infrastructure investments in emerging markets are ripe for take up by institutional investors.

3.3. Data and Methodology

3.3.1. Empirical model

A quantitative approach was adopted to evaluate the diversification ability and performance enhancement of infrastructure investments in a risky portfolio. The study used the correlation coefficient, portfolio optimization and the Sortino and Sharpe ratios in evaluating the capacity of infrastructure returns to enhance performance and reduce portfolio risk.

Correlation analysis is used to identify the extent to which series vary relative to each other over time. The traditional method to assess the diversification ability of an asset class is to carry out inter-class correlation matrix or bi-variate correlation calculations as used by Newell *et al.* (2011), Finkenzeller (2012), Oyedele, Adair, and McGreal (2014), De Bever *et al.* (2015), Kempler (2016), Bahceci & Leh (2017), and O'Brien & Leung (2018). The simple way of calculating the inter-asset correlation coefficient between any two assets is by means of the following formula;

$$\rho_{y,x} = {}^{\sigma_{y,x}}\!/_{\delta_y \,.\, \delta_x} - - - - - - - - - - - - - (3.1)$$

where $\rho_{y,x}$ represents the correlation coefficient between stock returns of Y and X indices, $\sigma_{y,x}$ is the covariance between Y and X, then δ_{i} is the standard deviation for Y and X. A small correlation figure (preferably a negative one) is evidence of the diversification ability of the assets under consideration (Kempler, 2016; Bahceci & Leh, 2017; O'Brien & Leung, 2018).

In emerging economies where portfolios are likely to be under-diversified (due to inefficient markets), the Sharpe quotient is the best absolute risk-attuned reward statistic (Kempler, 2016). This study employed the mean variance optimization procedures adopted by Oyedele (2015) Farrukh and Cherdantsev (2016) and Kempler (2016) in order to determine the optimal Sharpe ratios.

Considering our two portfolios (one with and the other without infrastructure), the objective was to identify a portfolio with the highest Sharpe ratio in each case (which is the optimal or tangency portfolio) and make some comparisons. We first determined the optimal portfolio without infrastructure noting its return and risk levels, and then add decomposed infrastructure (listed and unlisted) noting any changes in the resultant return and risk levels. Sharpe ratio is measured as follows:

$$S_r = \left(R_p - {}^{R_f}\!/_{\sigma_p} \right) \text{--------------------------------}(3.2)$$

where R_p represents portfolio yield, R_f denotes risk free rate and σ_p captures standard deviation of the portfolio. Large positive Sharpe fraction indicates greater risk-attuned performance, while small and/or negative quotient is a sign of disparaging returns. To compute returns, in an N-asset portfolio scenario we use the following formula:

$$R_p = \sum_{i=1}^{n} (W_i)(R_i) ------------ (3.3)$$

where R_i now captures average yield of the i^{th} asset in a portfolio and W_i is the proportion of i^{th} asset in the portfolio.

Variance of N-asset portfolio is computed as follows:

$$\sigma_{Rp}^2 = \sum_{i=1}^{n} W_i^2 \sigma_{ri}^2 + \sum_{i=1}^{n} . \sum_{j=i+1}^{n} 2W_i W_j Cov(ri, rj) --------(3.4)$$

As we increase number of assets in our portfolio, what remains as the key risk determinant is the covariance. The risk (variance) of a portfolio is computed using the following formula:

$$\mathrm{Var}\left(r_p\right) = \sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \mathrm{Cov}\left(r_i, r_j\right) ------------------------ (3.5)$$

Covariance articulated in terms of correlation factor is determined using the following mathematical expression:

$$\mathrm{Cov}\left(r_i, r_j\right) = \rho_{ij} \sigma_i \sigma_j = \sigma_{ij} ------------------------------- (3.6)$$

where ρ_{ij} = represents correlation coefficient between asset *i*, and asset *j* returns, whereas σ_i , and σ_j represents risk of asset *i*, and asset *j*, respectively.

In making straightforward the determination of the optimum risky portfolio (with and without infrastructure), we adopted the capital allocation line (CAL), portraying totally practicable risk-return combinations obtainable from diverse asset allocation selections. The aim is to identify asset proportions that give uppermost slope of the CAL (proportions resulting in the risky portfolio with the utmost Sharpe ratio) (Kempler, 2016). Restated, the aim is to get the best gradient of the CAL (Sharpe ratio) for every conceivable portfolio, X as presented in Fig 3.1 below:

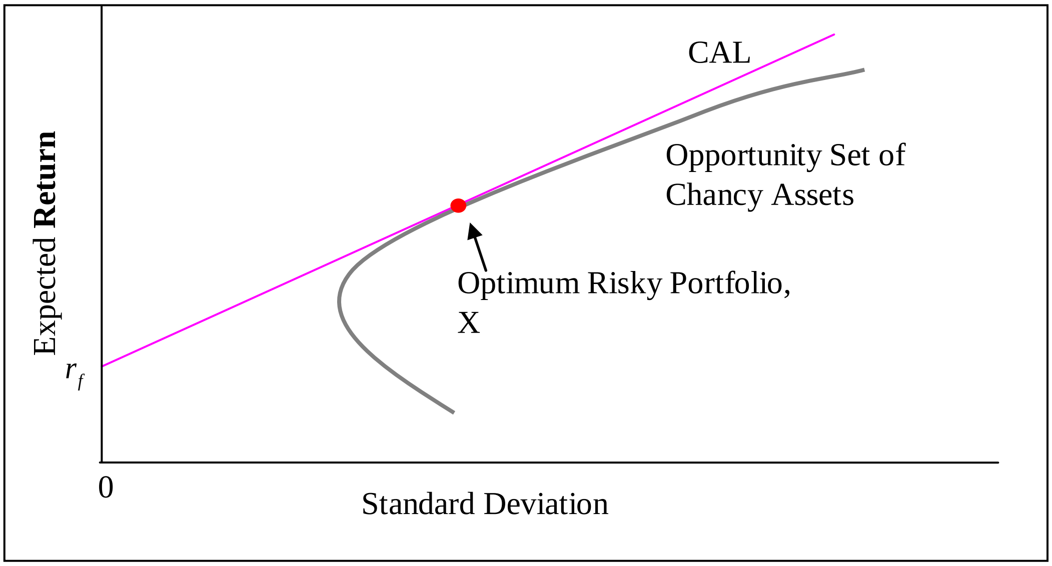

Figure 3.1: Optimal Risky Portfolio, X

In maximizing the objective function, CAL_S, there is need to meet the constraints that portfolio weights must add up to 1 and no short selling is acceptable, meaning that the individual asset class weight is always positive. Effectively, we find a solution to a computational problem strictly written as:

$$\underset{w_i}{Max}\ CAL_S = \frac{E(r_p) - r_f}{\sigma_p} \text{ ----------------------------(3.7)}$$

Conditional on: $\sum w_i = 1$.

The proportions of an optimal risky portfolio X, comprising two securities is determined as follows:

$$W_a = \frac{[E(r_a) - r_f]\sigma_b^2 - [E(r_b) - r_f]\rho_{ab}\sigma_a\sigma_b}{[E(r_a) - r_f]\sigma_b^2 + [E(r_b) - r_f]\sigma_a^2 - [E(r_a) - r_f + Er_b - r_f]\rho_{ab}\sigma_a\sigma_b} ----(3.8)$$

$$W_b = 1 - W_a --------(3.9)$$

As more than two assets are under study, such procedures were undertaken using Solver Microsoft Excel add-in to identify the optimal portfolio P (with and without portfolio). Under the Solver add-in, the Generalised Reduced Gradient (GRG) Nonlinear aligorithm which is fast, reliable and works well with nonlinear and linear problems, was used (Open Cast Lab, 2015). Comparing the risk and return levels from the optimal portfolios enables us to identify whether insertion of infrastructure investments into our investment portfolio dampen variance or enhances yields, if at all. Obtaining higher returns at low risk levels indicates the portfolio's ability to reduce diversifiable risk and enhance portfolio returns (Kempler, 2016).

To validate our results, we also applied the Sortino ratio (at individual asset level) which is closely related to Sharpe ratio presented above (see Equation 2). The two ratios are computed using the same formula, save a slight difference on how denominators are determined. On the Sharpe ratio, the standard deviation is an absolute measure (consider events above and below the mean or expected value) whereas under Sortino ratio, only cases or events below the mean or expected value are considered to be risky. Investors are generally wary of events below the mean relative to those cases where they earn returns above the mean. This substantiates the appropriateness of the Sortino ratio.

3.3.2 Data

The data was acquired from the Morgan Stanley Capital International (MSCI) for the years 2009-2018 (the post-crisis period) on a yearly basis. Prior to 2009, no unlisted or private infrastructure index was available to the general public. The MSCI's emerging market comprises the following twenty four nations: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, Qatar, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates. These nations represent 12% of global market capitalization (Moore, 2018). The variables of interest are highlighted below.

The emerging market infrastructure index (MSCI infrastructure emerging market index) captures listed infrastructure investments which are invested through exchange traded funds and common stock purchase. It was the proxy for listed infrastructure investments in this study. This index was used due to the difficulty of obtaining data on infrastructure sector returns at country level. The MSCI infrastructure emerging market index is made up of the following sectors: Telecommunications, Utilities, Energy, Transportation and Social infrastructure. The index is largely skewed in favor of telecommunication and electric utilities sectors as the sum up-to 60% of the total index weighting.

Given that it is claimed that features of listed and private infrastructure investments are different on short term basis (Wurstbauer & Schafers, 2015; Blanc-Brude, 2016, Howard, 2019), the MSCI Global quarterly private infrastructure index was treated as a representation for private or unlisted infrastructure investments. This means that, if the investment attributes of listed and private infrastructure are significantly different, investors can treat such investments as complementary; otherwise, they are substitutes (Kovarsky, 2018).

The MSCI emerging market general stock market index and MSCI emerging markets real estate index are the traditional risky asset classes that represent listed equity and listed real estate in emerging markets, respectively. Indices are tradable through the use of exchange traded funds and buying shares in listed firms. This will enhance a portfolio's liquidity, which is a primary concern for all investors (Chhabria *et al.,* 2014; Moss, 2014).

The ten-year government bond was adopted as an alternative for risk-free asset available to investors. It was selected as it fitted with the time period under study, and as a matter of convenience (Strydom & Charteris, 2009). The rate was taken as an average rate (from all 24 nations) in the calculation of the Sharpe and Sortino ratios as there was no readily available single risk free rate for the emerging nations under study.

3.4. Results and Discussion

This part spells out the results obtained.

3.4.1. Descriptive statistics

Using annual data on all variables, the general distribution of the data is offered in the table below.

Table 3.1: Measures of moments

	General equity	Listed infrastructure	Real estate	Unlisted infrastructure
Mean	11.51000	5.235000	8.783000	12.82700
Median	4.890000	2.675000	-2.850000	13.68000
Maximum	79.02000	35.43000	57.75000	17.20000
Minimum	-18.17000	-18.36000	-26.06000	4.700000
Std. Dev.	29.71952	16.42050	31.86879	3.400255
Skewness	1.162578	0.323772	0.691845	-1.304250
Kurtosis	3.639767	2.291655	1.772153	4.436276
Jarque-Bera	2.423188	0.383778	1.425918	3.694649
Probability	0.297722	0.825398	0.490192	0.157658
Sum	115.1000	52.35000	87.83000	128.2700
Sum Sq. Dev.	7949.251	2426.696	9140.575	104.0556

Source: Extract from Eviews computations

From Table 3.1, it can be noted that private or unlisted infrastructure earned more on average than other asset classes as it has the highest mean amounting to 12.287% per year. Listed infrastructure scored the least, with average returns amounting to 5.235% during the period under study. Private infrastructure had the lowest volatility or uncertainty as computed using standard deviation. Highest levels of volatility were noted in real estate, followed by general equity. This is an indication that private or unlisted infrastructure is the best asset among the available assets as it provided the maximum yields whilst exhibiting lowermost volatility points. In terms of normality, all the variables under study were normally distributed which augurs well for the assumptions of portfolio optimization and the Sharpe ratio.

The line graph below (Fig. 3.2) indicates how the asset classes in emerging markets trended from 2009 to 2018.

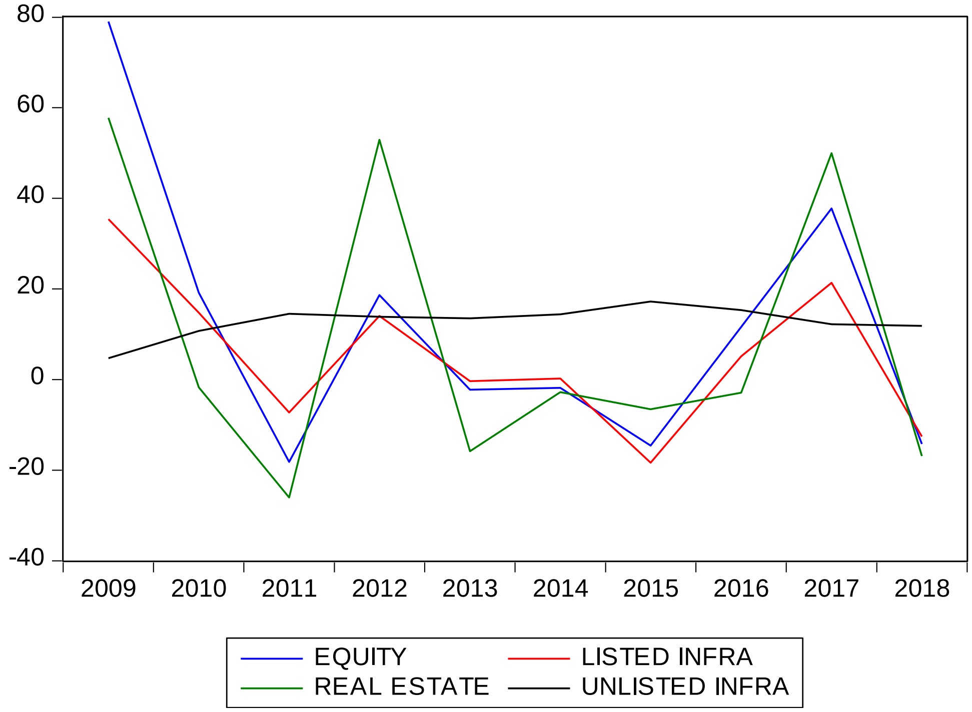

Figure 3.2*: Assets return trend (in %)*

It can be noted that all the assets are positively correlated as they moved in tandem during the period under study, save for private/unlisted infrastructure. Private infrastructure earned almost constant returns as opposed to all other asset classes under review. The level of difference in the distribution between private and listed infrastructure leads to the conclusion that the two investments are not substitutes but complement each other.

3.4.2. Bivariate correlations

In measuring the degree of linear relationship, correlation measurements are displayed in the table below:

Table 3.2: Bivariate correlation coefficients

	Equity	Listed infrastructure	Real estate	Unlisted infrastructure
Equity	1.000000			
Listed infrastructure	0.953461	1.000000		
Real estate	0.845761	0.824964	1.000000	
Unlisted infrastructure	-0.815844	-0.765006	-0.532175	1.000000

Source: Extract from Eviews

The correlation between listed assets (general equity, listed infrastructure and real estate) is positive and very high, indicating the existence of co-movement of returns over the period (as also indicated in Fig 3.2). This indicates that stock exchange players treat all listed assets homogeneously. In other words, euphoria and market swings affect all listed assets in the same direction due to the contagion effect. In contrast to Kempler (2016) and De Bever *et al*.'s (2015) findings, investing in listed infrastructure in emerging markets is similar to investing in any other listed stock—there is no immunity. The high levels of positive correlation among listed assets render diversification across listed assets ineffective. All listed asset classes are affected by market up and down turns, regardless of the fundamentals of the firms.

Private infrastructure exhibited negative correlation with all the assets under review, illustrating its ability to reduce risk in a mixed portfolio. This concurs with Bahceci & Leh's (2017) assertion that, portfolio risk reduction can be achieved by including private infrastructure into a risky portfolio comprised of exchange traded equities, listed real estate (property) and listed infrastructure in emerging markets.

The differences in the correlation coefficients scored by listed and private infrastructure are clear testimony to the claim that these are different and might not substitute for each other (Moss, 2014 and Stack, 2014). Interestingly, the correlation between listed and private infrastructure is negative to the tune of -0.7650, driving home the point that they are significantly different (De Bever *et al.*, 2015). This could be attributed to differences in liquidity, price transparency issues and risk-return profiles (Julian & Humphreys, 2016; and Langley, 2016). Market inefficiency could be another reason for this discrepancy as such inefficiencies are pronounced in emerging markets where information asymmetry remains an issue and the number of listed firms on stock exchanges is small compared to the entire economy (Carlson, 2020). In other words, the stock exchanges in most emerging markets do not reflect the fundamentals of the economy.

On a different note, advocates for behavioral finance are of the view that asset prices are affected by many factors other than the fundamental attributes of the asset (Statman, 2018). These include emotions and psychological biases and errors like the herd instinct and loss aversion. Since listed assets' prices are determined in the market, they are likely to be affected by these non-fundamental attributes on an on-going basis (Bruce, 2017). This might not be the case with private assets, which in most cases are tightly held and their pricing process are usually opaque. This does not imply that private assets are efficiently priced; rather, it simply means there is a significant difference between the two pricing processes. In a nutshell, publicly held assets are priced differently from privately held assets.

3.4.3 Individual asset risk-adjusted return

At individual asset level, the risk adjusted returns were computed using Sharpe and Sortino ratios and the ratios are shown in the table below:

Table 3.3: Risk adjusted returns

Asset	Sharpe ratio	Sortino ratio
Unlisted infrastructure	1.889	2.396
Listed infrastructure	-0.0713	-0.1122
Real estate	0.07462	0.1351
EM equity	0.1718	0.317

Source: Authors' extract from Microsoft Excel computations

At individual asset level, unlisted or private infrastructure equity earned highest risk-adjusted returns compared to other assets. Unlisted infrastructure proved to be an investment to reckon with as it earned way above the risk free rate in emerging markets. The difference between listed and unlisted infrastructure risk-adjusted returns further boggles the mind of rational economic man assuming that capital marketplaces are claimed to be informationally efficient in the current data and technology era. Listed infrastructure earned less than the risk free rate hence negative risk-adjusted returns. In other words, investors in listed infrastructure were not compensated for extra risk they assumed (which was above the risk in a risk-free asset). Real estate and general emerging markets listed equity generated returns exceeding the risk free rate indicating the existence of risk-premium on the two assets throughout the era studied.

3.4.3 Optimal portfolio risk-return profiles

Risk-adjusted yields from the optimal risky portfolios comprised of different assets were determined using the Sharpe ratio and portfolio optimization procedures. The returns were determined starting with a portfolio without infrastructure (listed and unlisted) as a base portfolio. The optimal risky portfolios' weights and corresponding Sharpe ratios are shown in Table 3.4 below;

Table 3.4: Optimal portfolio weights and Sharpe ratios

Asset	**Portfolio 1**	**Portfolio 2**	**Portfolio 3**	**Portfolio 4**
Real estate	0.00	0.00	0.00	0.00
Listed Equity	1.00	0.0881	1.00	0.0881
Listed Infrastructure	*Excluded*	*excluded*	0.00	0.00
Unlisted Infrastructure	*Excluded*	0.9119	*Excluded*	0.9119
Portfolio Return	11.51	12.71	11.51	12.71
Portfolio deviation	29.7195	1.7952	29.7195	1.7952
Sharpe Ratio	0.17177	3.5126	0.17177	3.5126

Source: Extract from Microsoft Excel

The assets considered in each portfolio were as follows;

Portfolio 1 - listed real estate, and listed general emerging market equity (base portfolio).

Portfolio 2 - listed real estate, listed equity, and unlisted infrastructure.

Portfolio 3 - listed real estate, listed equity, and listed infrastructure.

Portfolio 4 - listed real estate, listed equity, listed infrastructure and unlisted infrastructure.

Portfolio returns and the corresponding portfolio standard deviations from the optimal case for each portfolio are also shown in Table 3.4 for comparison purposes. A detailed analysis of Table 3.4 is presented below.

Portfolio 1 - listed real estate and listed equity

This was treated as the traditional or benchmark portfolio against which all other portfolios were measured. The optimal weight which maximized risk-adjusted returns was 100% for general emerging markets stocks and zero for real property investments. The subsequent Sharpe ratio amounted to 0.17177. In emerging markets, holding a portfolio comprising listed equity as well as listed real property does not add any value to institutional investors in the risk-return sense. Thus, before introducing infrastructure in this risky portfolio, rational investors earned optimal returns by investing all their capital in listed emerging market stocks, other things being equal.

Portfolio 2 - listed real estate, listed equity, and unlisted infrastructure

Adding unlisted or private infrastructure to a traditional portfolio proved worthwhile as the Shape ratio increased from 0.17177 to 3.5126. Portfolio returns increased from 11.51 % to 12.71%, indicating that private infrastructure effectively enhances portfolio returns. This concurs with Panayiotou & Medda's (2014) results. On the risk frontier, the resultant portfolio is less risky (1.7952%) relative to the traditional portfolio (29.7195%). This demonstrates the power of using negatively correlated assets to derive diversification benefits. Private infrastructure is excluded from the euphoria that often grips stock exchanges over time; hence, its returns are constant with low volatility (risk).

Portfolio 3 - listed real estate, listed equity, and listed infrastructure

In contrast to the conclusions reached by Oyedele (2015) and Daniel (2016), listed infrastructure and listed real estate behave the same. Hence, adding listed infrastructure to the traditional portfolio does not change either the portfolio risk or portfolio return in emerging markets. Adding listed infrastructure to a portfolio made up of listed real estate and listed general equity did not add any value to the portfolio. Portfolio 3 and portfolio 2 provided same results. Thus, unless other factors besides risk and return are considered when making the asset allocation decision, there is no value in including exchange traded infrastructure into portfolios made up of listed real estate and general equity in emerging markets.

Portfolio 4 - listed real property, exchange traded equity, listed infrastructure and unlisted infrastructure

Overall power of improving returns and reducing portfolio risk by investing in private or unlisted infrastructure is evident in this portfolio made up of all the asset classes under consideration. Portfolio 4 resembles all aspects of portfolio 2 as the risk-adjusted return is maximized by allocating funds to unlisted infrastructure and general equity in emerging markets. Unless investors are pursuing other goals besides risk and return, there is no rational economic reason to take in exchange traded infrastructure assets and real property in their portfolios in emerging markets.

3.5. Conclusions and Recommendations

Using yearly data from 2009 to 2018 (the post-crisis period) from emerging markets, applying Sortino ratio, portfolio optimization and the Sharpe ratio, it was evident that private or unlisted infrastructure was a return enhancer and portfolio risk diversifier. Founded on the study's outcomes, it can be safely resolved that listed and unlisted infrastructure complement each other as they exhibited significantly different risk-return profiles which can be manipulated by institutional investors for positive returns. This is driven mostly by the heterogeneous features obtaining in private and public financial markets.

It was found that listed infrastructure did not add any value in a traditional portfolio made up of listed real estate and general equity in emerging markets. Given that listed infrastructure and other listed assets are positively correlated, they can be treated as substitutes. Unless institutional investors are concerned with factors besides risk and return when making asset allocation decisions, there is no value in including listed infrastructure in a traditional portfolio.

Based on these findings, institutional investors are encouraged to consider the heterogeneous nature of infrastructure when investing. Subsector analysis might also add value given the heterogeneous nature of the infrastructure sector. The same can be said of emerging markets which are also heterogeneous, implying that generalizations might be problematic. This study thus serves as a forerunner study on infrastructure investments role to investors in developing economies.

It is also recommended that institutional investors monitor developments in the infrastructure market on an on-going basis due to the fact that, as the sector grow and mature, increased deregulation and privatization become the order of the day, calling into question its ability to deliver superior returns. Firms in the infrastructure sector should make more information available to the public so that their assets are rationally priced. Restated, infrastructure firms should be wary of the way their fundamental assets are priced in financial markets. It should not be assumed that a firm's value will be volatile (and lower) simply because it is listed whilst its equivalent counterparties are stable because they are privately held. Such inconsistencies might affect the firm's credit rating as well as merger and acquisition values.

The findings of this study imply that investors should not expect financial rewards for investing in listed infrastructure if they have already invested in general equity in emerging markets. Another implication is that exchange traded and private infrastructure investments need to be considered like complementary assets as their stochastic behavior and risk-return profiles are expressively different. Given the positive part and function played by private infrastructure in a risky portfolio, institutional investors are capable of achieving their 'performance seeking' goals using unlisted infrastructure.

On the academic front, longer time frame might be useful in further explaining the role of infrastructure to investors in emerging markets given that the sector is still developing. On the same note, other risk-adjusted return measures like the Jensen's Alpha could be considered in future researches.

The main contributions from this paper are three fold. Firstly, it highlighted the infrastructure sector investment features in emerging markets (post-global crisis period) which were generally neglected from past studies. The paper confirms the portfolio risk diversification and return enhancing abilities of unlisted infrastructure. Secondly, it used both absolute and down-side risk-attuned yield measures in evaluating the ability of infrastructure investments to earn superior returns and diversify portfolio risk. Related to this, the paper used a plethora of tests in-order to validate the findings from emerging markets whereas most industrial bulletins and few academic papers used few elementary tests.

Lastly, it confirms the claim that listed and unlisted infrastructures are significantly different—thereby providing some valuable insights when it comes to asset allocation and portfolio revision decision making. It was noted that unlisted infrastructure provides investors with better yields and reduces portfolio risk better than listed infrastructure. As such, exchange traded and private infrastructure assets can be part of the same portfolio giving the holder some diversification benefits.

Authors' contributions

Rabson Magweva- Magweva is the main author of the paper presented above. As a PhD student it was his role to formulate the objectives, review literature, and come up with the proper methodology to achieve set objectives and coming up with the final write up.

Mabutho Sibanda- Sibanda is the academic supervisor and as such he gave valuable insights into the contents of the papers and provided comments before the papers were sent to the journal for academic review and publication.

CHAPTER 4

INFRASTRUCTURE INVESTMENTS AND INFLATION HEDGING AND MANAGEMENT IN DEVELOPING ECONOMIES

As a hallmark of infrastructure investments, inflation hedging ability was thoroughly evaluated using linear and non-linear approaches. As such, three papers were drawn to fully evaluate this claimed infrastructure investment feature. The first paper used the linear model and the second paper used a non-linear approach. The third paper adopted the panel data approach in evaluating the capacity of infrastructure investments to hedge inflation in comparison to related asset classes. The first paper is still under review whereas the second and the third papers were published.

4.1. Chapter introduction

All investments are characterized by different levels of risk and uncertainty. Risks like exchange rate, interest rate and political factors deter investors from realizing their short term and long term objectives (Brenchley, 2019). Worldwide, the preservation of purchasing power is one of the key objectives pursued by individual and institutional investors (First State Investments, 2018). As noted by Briere and Signori (2011), inflation risk is one of the worst and most devastating macro-economic enemies of investors, savers and pensioners. Resultantly many institutional investors like insurers and pension funds set their long term returns in a manner that they aim to surpass the consumer price index (CPI) (First State investments, 2018). Identifying an asset which hedges inflation risk is thus paramount (Naser 2017; Brenchley, 2019). Subsequently, investors opt for diversified portfolios and hire active asset managers in an attempt to protect their wealth from inflation, among other risks (United Nations Conference on Trade and Development [UNCTAD], 2012; Austin & Dutt 2016; Lopez-Martin, Leal & Martinez, 2017).

The hunt for better assets in terms of performance and risk reduction is always on regardless of the economic environment (World Banks, 2018b; Carlson, 2019). Identifying the best asset allocation is crucial for risk-averse investors (especially long-term ones) as they face significant challenges in maintaining the real value of their possessions as time progresses and in achieving yields high enough to meet investors' long term portfolio aims and objectives (Austin & Dutt, 2016). An asset or a commodity is treated as an inflation hedge (preserves purchasing power) when its real return or yield is constant (Mugambi & Okech, 2016; Naser, 2017). In other words, the asset is generating real yields which are free of the prevailing rate of inflation, thereby entailing a positive link between the asset nominal yield and the inflation rate over the specified time period (Naser, 2017).

While numerous studies have evaluated different commodities and asset classes' ability to hedge inflation, the results are inconclusive (Phiri, 2016; Huthaifa, 2020). The current study concentrates on the 'hot topic' of the moment – infrastructure- evaluating its ability to stand as a better asset compared to traditional assets. The infrastructure market is still at its infancy in emerging markets, implying that inflation hedging capabilities in these markets could differ from those in developed countries (Asayesh & Gharavi, 2015). The infrastructure market in developed nations is mature and has been under deregulation and privatization phase for some time. This tends to reduce the monopoly powers once present in the sector (Swedroe, 2013). Subsequently, superior returns and inflation hedging capability in developed markets might be under threat as more private players participate in the sector. This is not the case in developing nations where the level of risk in the sector is high therefore calling for risk premiums to induce investors to move capital into the infrastructure sector (Isnandari & Chalid, 2017).

The favourable economic and regulatory features of infrastructure investments suggest that they are well-placed to offer inflation-linked returns and less volatile cash inflows (Burke, 2017; Howard, 2019; Riding & Emma, 2019). Demand for infrastructure products and services tend to be inelastic, giving firms some pricing edge whereby they can pass on costs to the final consumer (Nassar & Batti, 2018). In many infrastructure markets, the hurdles to entry are facilitated by laws of the nation, the geographical distribution of the resources, high capital requirements and unavailability of substitutes (Burke, 2017; Hulbert, 2019).

The infrastructure sector has the potential to serve as a sound inflation hedge as it can deliver steady, low-volatile and predictable inflation-linked cash-inflows due to its monopolistic and oligopolistic character, at least theoretically (World Bank, 2018b; Brenchley, 2019). This sector provides essential, difficult-to-substitute goods and services with inelastic demand whose prices are linked to inflation by concessions and agreements. The economic and financial characteristics of the infrastructure sector (derived from its oligopolistic and strategic pricing powers) make it better placed than other sectors when it comes to adjusting prices in line with changes in inflation (UNTT, 2015; Wurstbauer & Schafers 2015). However, deregulation is watering down these powers (Swedroe 2013).

In times of financial turmoil, it might be possible to increase the price per unit, but depressed demand could result in decreased sales, resulting in the same earnings as before and after an inflation-adjustment in price (Brenchley, 2019). For various reasons, the inflation hedging capabilities of infrastructure investments is debatable, especially in emerging markets where the deregulation drive is gathering momentum.

The inflation hedging capacity of an asset is evaluated using inflation beta (inflation coefficient in the regression model) as specified by the Fama & Schwert (1977) model. The coefficient is symmetric when linear models are used; implying that inflation increases and decreases have the equivalent effect on nominal asset returns Davari & Kamalian (2018). However, given the non-linear nature of economic relationships, linear models are not always appropriate in assessing the hedging capacity of different asset classes (Davari & Kamalian 2018; Katrakilidis, Lake & Emmanouil 2012). This study applied both linear and non-linear approaches to fully expose the inflation hedging capacity of infrastructure in emerging markets.

The paucity of academic studies on infrastructure investment is astounding. Few academic papers that mainly focus on the UK, the US, and Australia are available (Peng & Newell 2007; Martin 2010; Sawant 2010; Rodel & Rothballer 2012; Birdet *et al.*, 2014). Furthermore, most previous studies used basic statistical measures like mean return, and correlation coefficient as measures of the inflation hedging ability of infrastructure investments, (Davari & Kamalian 2018). The findings reported by previous researchers are in tandem with the two main theories hypothesizing the connection between security yields and inflation shocks. The leading proposition is the Fama & Schwert (1977) model which stipulates that equity yields do withstand inflation shocks, implying a positive significant relationship. The second theory is the "proxy hypothesis" by Fama (1981) which specifies the reality of an inverse connection amid equity yields and general price increase.

This present study sought to reduce this fissure in the academic literature by evaluating the inflation hedging capability of infrastructure investments in emerging nations on short and long term basis. For comparison purposes, we also scrutinized the capacity of real property and general listed equity to act as inflation hedges in emerging markets applying robust econometric methods. The study applied Autoregressive Distributed Lag (ARDL), non-linear ARDL (NARDL) and Panel ARDL models.

The remainder of this present research paper is prepared in the following manner: the ensuing unit exposes the theoretical and empirical literature on the inflation hedging abilities of infrastructure and other asset classes. The third part discusses the approaches adopted, whilst the fourth unit details the study's findings. The paper ends with overall conclusions and recommendations to investors and researchers. Implications of the findings and conclusions made are also addressed in the last section of the research paper.

4.2. Literature review

Stock returns' ability to hedge inflation is hinged on the ability of the firm or sector in question to increase its prices in tandem with inflation (Asayesh & Gharavi, 2015). Investor sentiments and expectations matter when it comes to the valuation of shares and corresponding returns (Statman, 2018). The 'inflation illusion' bias which affects investors leads to lower stock returns during inflationary periods (Briere & Signori, 2011). This is established on the element that investors tend to overvalue the impact of inflation on current stock and firm value and undervalue the firm's ability to increase its nominal earnings value in line with inflation (Wurstbauer & Schafers 2015). Therefore, instead of the effects cancelling one another out, stock prices tend to drop as investors sell their holdings due to bearish sentiment in an inflationary environment. In a nutshell, the connection between nominal equity yields and general price increases tend to be negative (Adusei, 2014).

The effect of inflation on stock returns is two-fold. Firstly, nominal cash inflows or earnings increase as firms adjust their prices in line with inflation trends (Wurstbauer & Schafers, 2015). Secondly, uncertainty regarding future earnings increases, putting upward pressure on the discount rate or premiums required by providers of capital and reducing the stock and firm value (Lee, 2014). Depending on the net effect of inflation on future earnings and discount rate, stock value/returns might increase or decrease as inflation soars (Paula, 2017).

The theoretical literature on inflation hedging is premised on the Fama-Schwert model of 1977, which is projected to exist in long term scenarios. Derived from generalized Fisher hypothesis of 1930, this model assumes a significant positive relationship between asset return (in nominal terms) and inflation rate, implying that asset returns hedge inflation and that nominal stock return moves in step with inflation over time (Chang, 2013). The impact of inflation on nominal cash-inflows is greater than its impact on the discount rate and investors' bearish sentiments, thereby increasing the value of the firm and corresponding stock returns.

At the extreme end of the spectrum on stock's ability to absorb inflation risk is the 'proxy hypothesis' proposed by Fama (1981). This posits that an inflationary economic environment is a signal of unstable, depressed economic activity and a bleak future for firms, threatening corporate survival. As such, the link between the rate of general price increases and nominal equity yields is expected to be negative (Akturk, 2014). As remarked by Bodie (1976), the negative relationship between general price rise and equity yields implies that an investor must short-sell stock to hedge inflation. This suggests that the net effect of inflation on the discount rate is higher than its effect on nominal earnings. In the same vein, an inverse link between equity returns and price rises implies that “inflation illusion” and irrationality among investors are more pronounced, pointing to the inefficiency of financial markets (Statman**,** 2018).

Empirical studies on equity yields and general price increases are in support of both the Fama-Schwert model (see Incekara, Demez, & Ustaoglu, 2012; Emenike & Nwankwegu, 2013; Ibrahim & Agbaje, 2013) and the proxy hypothesis (Gul & Acikalin, 2008; Lee, 2010; Tripathi & Kumar, 2014). The positive and negative relationships among equity yields and rate of general price surge could be a function of inflation rate type during the period under review. Creeping inflation (less than 3%) is often associated with improved company performance and real growth in Gross Domestic Product (GDP). Thus a third hypothesis can be proposed that captures the non-static link between inflation rate and equity yields (and commodity prices). At low inflation points, (below 3%) the relationship is positive, while at high levels (above 10%), it becomes negative. Consequently, assets, which hedge inflation at low inflation levels, might not do so at high levels (Hulbert, 2019; Mercadante, 2019).

Turning to the infrastructure sector, in particular, Chhabria *et al.* (2015) noted that infrastructure firms operate in a market with high barriers to entry. This tends to result in inelastic demand as the sector mainly provides utilities, thereby reducing commodity price risks and enhancing strong, steady cash flows (Inderst & Stewart, 2014). The prices of the products and services rendered by such firms tend to be indexed to economic rates such as inflation (Peng & Newell, 2007; Huthaifa, 2020). Thus, firms can generate inflation-hedged revenue and earnings (Blanc-Brude 2018). The question is thus whether capital markets can transpose the inflation hedging features of the infrastructure sector into stock prices and stock returns.

It is, however, important to note Blanc-Brude’s (2015) observation that the intrinsic features of infrastructure assets are most pronounced in developed markets. This calls for a deeper analysis of emerging markets where the infrastructure market is still rudimentary. On the same note, the infrastructure sector is socially, and politically sensitive, which might call for government intervention during inflationary periods (Martin, 2010). In other words, the pricing power of an infrastructure firm might be undermined at the time when it is most needed (Carlson, 2020). Even if the sector can adjust the prices of final products, the cost of inputs like commodities and capital is likely to rise (Chang 2013). In such a scenario, the sector will only be able to hedge inflation if it can increase the price of outputs at a faster rate or percentage than the price of inputs.

The few academic studies on this subject have produced mixed results using basic statistical methods. Wurstbauer & Schafers (2015) concluded that, in the United States (US), direct infrastructure investments have a measure of inflation (general price increase) hedging capability on short term phase but are a sound inflation hedge on the long term phase. In line with these findings, Colonial First State's (2009) examination of the top five Australian infrastructure funds suggested that infrastructure investment offers inflation protection as the returns were positive and above the inflation rate.

In contrast, Peng & Newell (2007) found a negative (though insignificant) relationship between infrastructure investments (listed and unlisted) and inflation in Australia. This agrees with Martin's (2010) findings on listed infrastructure firms in the US and Rodel and Rothballer's (2012) results on listed infrastructure firms in 45 nations. Bitsch, Buchner, and Kaserer (2010), Sawant (2010), and Bird *et al.*, (2014) produced insignificant results using data from the US and Australia.

Given the on-going debate on the infrastructure sector's ability to hedge inflation, it is important to conduct empirical studies in emerging markets where the infrastructure market is in its infancy, infrastructure needs far outweigh supply, and there is high inflation, political and settlement risks (World Bank, 2018b). Most emerging economies have a narrow range of assets which can be used by domestic investors, amplifying the quest for inflation hedging assets (Rodel and Rothballer, 2012).

4.3 Empirical model and Methodology

4.3.1. Empirical models and estimation techniques

In line with Wurstbauer and Schafers (2015) and Arnason and Persson (2012), this study utilized the model by Fama & Schwert (1977). The econometric expression is hinged on the Fisher (1930) proposition, which assumes that the nominal rate of interest comprise of the real rate added to inflation. Transposed to asset returns, the empirical model is structured as follows;

$$R_t = \alpha + \beta I_t + \varepsilon_t \quad ---------- (4.1)$$

where R_t captures asset class nominal return at time period t, I captures actual inflation rate, α is the real return and ε denotes the error term, whereas the β (inflation beta) explains whether an asset is a negative or positive inflation hedge, if at all (Wurstbauer & Schaufers, 2015). When the inflation beta is not more than one but expressively poles apart from zero, the asset or security is a partial inflation hedge. The beta coefficient can be equivalent to one, indicating that the security can act as a perfect/complete general price increase hedge, and when the coefficient is larger than one, the asset is more than a perfect inflation hedge (Isnandari & Chalid 2017).

Generally, the influence of regressors on the regressand in most economic and financial cases takes time to take effect. In other words, the dependent variable responds with a lag (after some time). A change in the independent variable, like money supply will effectively affect the dependent variable, like exchange rate after some weeks if not months (Ghouse *et al.*, 2018). Adjustment is unlikely to be instantaneous due to slower information dissemination, irrational investors and the informational inefficiency that characterize emerging markets (Babatunde, 2017). On the same note, economic variables tend to be serially correlated because of their time series nature (ordered nature), inertia and momentum effect (Nkoro & Uko 2016). As such, static models will fail to reveal the relationships among variables and an autoregressive (dynamic) model is appropriate.

Economic variables tend to be non-stationary in nature, and differencing the variable is the common remedy for non-stationarity. Differencing the variable leads to loss of long-term association amongst the variables under consideration; hence, a model which retains both short- and long-run is appropriate, even after differencing the variables (Mallick, Mallesh & Behera 2016: Mustafa & Selassie, 2016). Traditional long-run models such as Johansen & Juselius (1990) require that variables be stationary in the same level. In most instances, this is not the case; thus, a model which estimates long-run relationship using variables integrated of mixed orders is required (Babatunde, 2017). The autoregressive distributed lag (ARDL) model suits all these features of economic series (Pesaran *et al.*, 2001; Davari & Kamalian 2018).

Observing the long-term feature characterizing most underlying infrastructure assets and projects, it is interesting to expand the view beyond short-term hedging mechanisms. Therefore, an approach that recognizes and separates short and long-term effects is most appropriate. Financial markets tend not to modify promptly to shocks in prices and other macro-economic variables due to lengthy transaction times, irrational investors and informational inefficiency. As such, it seemed dubious that a non-dynamic regression model would adequately identify all rejoinders from different asset classes to inflation. A model which captures the impact of lagged regressor variables on the regressand variable is appropriate (Huthaifa). On the same note, due to inertia, persistence and the momentum effect that are rampant in stock markets, a dynamic model best suited the variables under study.

Given the above arguments, this present study adopted an autoregressive distributed lag (ARDL) bound testing specification postulated by Pesaran, Shin & Smith (1999), as extended by Pesaran, Shin & Smith (2001) to expose short and long term relationships between asset classes and the actual inflation rate. This method commonly affords unprejudiced estimates of the long-term model and reliable t-statistics even if some of the independent variables might be endogenous and the population is small (Nkoro and Uko, 2016). On the same note, the ARDL model is less likely to suffer from spurious regression emanating from missing variables and it is conceivable that the regressand and the regressors can have different optimum lags lengths (Ghouse, Khan, and Rehman 2018).

Equation 4.1 above considers only one independent variable (inflation). In the present case, there are three independent variables (hereunder captured as *X, Y* and *Z*). Therefore the empirical model is represented as an ARDL (*p*,*q*) model of Equation 4.1 as follows:

$$\Delta Y_t = \alpha + \sum_{j=1}^{p} \delta_i \Delta Y_{t-j} + \sum_{j=0}^{q} \gamma_i \Delta X_{t-j} + \sum_{j=0}^{q} \varphi_i \Delta Z_{t-j} + \beta Y_{t-1} + \lambda X_{t-1} + \vartheta Z_{t-1} + \varepsilon_t \quad ---(4.2)$$

where Δ represents a first difference operator, *p* and *q* are the optimum lag length for dependent variable (asset class returns) and independent variables (actual inflation rate and control variables) respectively. The parameters δ, φ and γ are the short-run dynamics and the coefficients β, ϑ and λ represent the long-term dynamics of the approach, whereas ε_t is the usual white noise residuals. *Y* is the nominal returns of the asset class under study whereas *X* is the actual inflation rate and *Z* captures the control variables. The significance of the parameters γ and λ determines the degree to which the asset class under study hedges inflation in the short and long term respectively. As there are three asset classes under study (real estate, common stock and infrastructure), and the decomposition of infrastructure investment into listed and unlisted categories, four models were estimated.

The study also made use of the re-parameterized Equation 4.2 as evidence from the bounds tests results indicated the existence of long run relationship among variables (Asghar *et al.*, 2015). The resultant error correction equation is represented as:

$$\Delta Y_t = \alpha + \sum_{j=1}^{p} \delta_i \Delta Y_{t-j} + \sum_{j=0}^{q} \gamma_i \Delta X_{t-j} + \sum_{j=0}^{q} \varphi_i \Delta Z_{t-j} + \theta EC_{t-1} + \varepsilon_t \quad ----(4.3)$$

whereby θ denotes the speed of adjustment towards long term equilibrium and EC is the error correction term (residuals are from long-run estimation). All other parameters are similar to Equation 4.2 above. The coefficients for inflation and control variables are expected to be positive and significant in all models. The coefficient of the error term is expected to be negative and significant evidencing the existence of long run relationship among variables.

One constraint of the ARDL approach is its supposition of linearity between the regressors and the regressand. This assumption does not hold in most financial and economic relationships as the variables are subject to violent fluctuations as well as structural breaks, and exhibit non-linear behaviour (Po & Huang 2008; Anoruo 2011; Saeed, Chowdhury, Shaikh, Ali, & Sheikh 2018). The linear ARDL model ignores the likelihood that increases and decreases in the regressors have a different impact and effect on the regressand (Nasr, Cuna, Demirer, & Gupta 2018; Saeed *et al.* 2018). For these reasons it is logical to assume that positive and negative changes in inflation rates do not have the same effect on asset earnings. If inflation increases, firms tend to respond quickly by adjusting the prices of their products and services upwards (Huthaifa). In the case of a fall in inflation, they tend to adjust prices at a slower pace, if at all.

Previous studies on the general price increases protection abilities of different security classes produced mixed results - with both a positive and negative effect reported (Phiri, 2016; Huthaifa, 2020). This drives home the need for an asymmetric model which captures and separates positive and negative effects as a change in inflation might have an inverse influence and sometimes an affirmative impact on stock returns. Traditional linear models assume that the dependent variable responds equally (in a symmetric manner) to both increases and decreases in the independent variable (Bildirici & Turkmen 2015; Saeed *et al.* 2018).

To address the issues highlighted above as well as the technical drawbacks of linear models, the study adopted an NARDL model suggested by Shin, Yu, & Greenwood-Nimmo (2014). The model makes use of positive and negative partial sum decompositions, thus permitting the exposure of the asymmetric (non-linear) impacts on long and short term basis. It must be emphasized that this nonlinearity or asymmetry is not similar to the logic that the coefficients are quadratic or log-linear as is frequently the norm. Rather, it is a disintegrated linear link on the impact of the regressor variables on the regresssand in ARDL to ascertain whether increases and decreases in the regressor have a dissimilar influence on the regressand variable (Shin *et al.* 2014). As indicated by Bildirici & Turkmen (2015), asymmetry is one type of non-linearity. Under the NARDL model, a nonlinear association is a kind of connection between two variables whereby an adjustment in one variable does not match with persistent and symmetric adjustment in the other variable (Bildirici & Turkmen 2015).

The NARDL model is simply an asymmetric extension of the standard ARDL model to capture and estimate short- and long-term associations (Babatunde 2017; Nasr *et al.* 2018). In other words, once the negative and positive partial sums of inflation are added in Equation 4.2 above (ordinary ARDL model) it becomes a nonlinear ARDL model (Saeed *et al.,* 2018). The model corrects for endogeneity and serial correlation and is very simple to estimate. Katrakilidis & Trachanas (2012) argues that NARDL outclasses in capturing long-run link in minor sample sizes, which hold water in this study. The NARDL model allowed us to capture the hidden cointegration (non-linear cointegration), which is impossible with traditional techniques as they are based on the actual data and not the data disintegrated into its positive and negative parts (Nasr *et al.* 2018). NARDL models are applicable irrespective of whether the regressors are integrated of different orders. To avoid incorrect estimates and invalid F-bounds tests, variables integrated of order two should not be used in a NARDL model (Chigusiwa, Bindu, Mudavanhu, Muchabaiwa & Muzambani 2011; Ibrahim 2015). This indicates the need to perform unit root or stationarity tests on the variables.

To fully expose possible asymmetric impacts of general price increases on asset returns, the inflation rate is disintegrated into partial sums of positive and negative changes in the rate. The resultant NARDL short-run model is expressed in the following manner:

$$\Delta R_t = \alpha + \sum_{i=1}^{p-1} \delta_i \Delta R_{t-i} + \sum_{i=0}^{q} \gamma_i \Delta INF_{t-i}^{+} + \sum_{i=0}^{q} \emptyset_i \Delta INF_{t-i}^{-} + \sum_{i=0}^{q} \varphi_i \Delta \mathrm{Z}_{t-i} + \varepsilon_t --- (4.4)$$

INF_t^+ , denotes partial sum of positive adjustment in inflation, INF_t^- captures partial sum of negative adjustments in inflation. The parameters γ_i and $\emptyset$ capture the ability of the asset class in question to hedge positive and negative changes in inflation. All other parameters remain the same as in Equation 4.3. The corresponding long run NARDL expression is captured using the following expression:

$$R_t = \alpha + \beta R_{t-1} + \lambda INF_{t-1}^{+} + \omega INF_{t-1}^{-} + \vartheta Z_{t-1} + \varepsilon_t --- (4.5)$$

λ, captures the ability of the asset return in question to hedge positive inflation shocks in the long run, and ω specifies whether the asset class in question can hedge negative inflation changes on long term basis. The partial sums of positive and negative processes of inflation, respectively, are expressed as follows:

$$INF_t^{+} = \sum_{i=1}^{t} \Delta INF_t^{+} = \sum_{i=1}^{t} \max(\Delta INF_i, 0) --- (4.6)$$

$$INF_t^{-} = \sum_{i=1}^{t} \Delta INF_t^{-} = \sum_{i=1}^{t} \min(\Delta INF_i, 0) --- (4.7)$$

Shin *et al.* (2014) noted that Pesaran *et al.*'s (2001) bounds testing approach is applicable and functional for Equation 4.5. The bounds test is applied to compute an F-statistic to determine whether there is a substantial link between asset yields and general price increases (if there is a long term connection between them). In the case that F-statistic is lower than the critical values (in absolute terms), we fail to reject the null hypothesis, thereby indicating the absence of a long-term effect. In contrast, when the F-statistic is greater than the critical values (in absolute terms), we fail to accept the null hypothesis (Davari & Kamalian 2018).

The study also used panel data to sufficiently expose the capacity of infrastructure to hedge inflation shocks in emerging nations. Economic variables tend to respond and affect other variables with a lag due to inertia, transmission mechanisms and momentum effect that are most pronounced in capital markets. This calls for dynamic model application in determining the relationships amongst the variables under consideration. The common estimator used for dynamic panel data is the generalized method of moments (GMM) (Arellano, 1989; Arellano & Bover, 1995). GMM is well-suited for panels with many units of interest and a small number of observations per unit. For a larger number of observations and small cross-sections, as in this study, the GMM estimator can produce inconsistent, spurious and incorrect estimates (Pesaran *et al.*, 2001; Nahla, Fidrmuc & Ghosh, 2013). Thus, in our heterogeneous panel data setting, we adopted the Panel Autoregressive Distributed Lag (PARDL) following Kutu and Ngalawa (2016) and Fazli and Abbasi (2018). The study applied panel data as it gives more explanatory power, less collinearity, offers more degrees of freedom, caters for heterogeneity and is more proficient relative to time series and cross-sectional data (Baltagi, 2008; Hsiao, 2014; Kutu & Ngalawa, 2016).

The PARDL derives most of its merits from the traditional ARDL model. These include the fact that it can simultaneously estimate short- and long-run dynamics, can be used in a case of mixed order of integration (but not on variables integrated of order two or above), and different lags can be used on different variables (Shin *et al.*, 2014). Another key merit of PARDL is its compliance with both small and large sample sizes (Rafindadi & Yosuf, 2013; Kutu & Ngalawa, 2016). The current study made use of three alternative approaches (for comparison purposes, reliability and validity), explicitly we used the mean group (MG), pooled mean group (PMG) and dynamic fixed effects (DFE) estimators. These three estimators use the maximum likelihood approach and capture the long-term equipoise and the heterogeneity of the dynamic adjustment progression (Onuoah *et al.*, 2018).

The MG approach approximate distinct equations for every cross-sectional unit and computes the coefficient means, thereby providing consistent estimates of the average of the parameters although neglecting the point that certain coefficients may be homogeneous across the units. Effectively, MG estimator is the least constricting, as it tolerates for the heterogeneity of both short- and long-term parameters (Fazli & Abbasi, 2018). The DFE estimator restrains the long-term coefficients to be similar across the cross-sections. Furthermore, it constrains the short-term parameters, together with the error correction term to be homogeneous. Only the individual intercepts may differ freely (Nahla *et al.*, 2013; Fuinhas, Marques, & Koengkan 2017).

The PMG approach constrains the long-term factors to be homogeneous across entities (similar to DFE), and like the MG estimator, permits the short-term coefficients, speed of adjustment, intercepts and the error variances to be different freely across the entire cross-section (Fazli & Abbasi 2018;

Onuoah *et al.*, 2018). PMG, as well as MG, provide reliable coefficients regardless of the potential existence of endogeneity as they include the lags of the regressand and regressors (Pesaran *et al.*, 1999). As is evident from the brief outline, the PMG is more of the middle of the road approach to heterogeneous panel data estimation.

The general PMG is of the following empirical structure (Lee & Wang, 2015):

$$Y_{it} = \sum_{j=1}^{p} \lambda_{ij} Y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}' X_{i,t-j} + \mu_i + \varepsilon_{it} \text{ ------}(4.8)$$

where, Y_{it} denotes return for the asset in question (infrastructure, real estate and composite listed stock) for country i, X_{ij} (k x 1) is the vector which captures the actual inflation rate and control variables as specified above. δ_{ij} are (k x 1) coefficient vectors. Emerging nations are symbolized by i = 1, 2, …,N, whereas time periods are denoted by t = 1,2,…,T. The parameter μ_i represents fixed effects, and ε denotes the normal residual term. The lags included in the model are captured by p and q for regressand and regressors, respectively (Lee & Wang, 2015). The study adopted a re-parameterized Equation 4.8 structured as follows:

$$\Delta Y_{it} = (\varphi_i Y_{i,t-1} + \beta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta Y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*\prime} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \text{ --- } (4.9)$$

Where $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$, $\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}$, $\beta_i = \sum_{j=0}^{q} \delta_{ij}$, $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}$ whereas $\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im}$

4.3.2. Data and variables of interest

Time series data (for ARDL and NARDL) and panel data (for PARDL) were used in this study. The study used quarterly data from Morgan Stanley Capital International (MSCI), solely based on the fact that it provided the key variables required in this study. The data is available for the emerging market category at index level. MSCI uses 24 emerging nations to come up with its indices, namely, Brazil, Peru, Chile, Columbia, Mexico, Czech Republic, Egypt, Hungary, Poland, Qatar, Russia, South Africa, Turkey, United Arab Emirates, China, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Taiwan, Greece and Thailand.

The MSCI Emerging market infrastructure index captures listed infrastructure in the emerging nations given above. The stocks are from companies that are directly involved in the provision of a primary infrastructure product or service namely; energy, utilities, telecommunication, social and transport sectors. The index is highly skewed towards the telecommunication sector.

The MSCI Global quarterly private infrastructure index also referred to as the IPD global quarterly infrastructure direct asset index, captures unlisted infrastructure investments. The global private index was used due to the unavailability (to the public) of unlisted or private infrastructure returns data in emerging markets. From the literature reviewed above, it seems that exchange-traded and private infrastructure securities are significantly different in their stochastic behaviour; hence, the decomposition was deemed fit in this study. For comparison purposes, this study examined the asymmetric hedging abilities of general listed stocks and real estate in developing using the MSCI Emerging market stock market and MCSI Emerging market real estate indices, respectively.

The average consumer price index (CPI) from the 24 emerging nations was treated as a true representative for the general price increase in developing economies. The gross domestic product (GDP) growth rate and global Brent crude oil price changes were treated as control variables.

Monthly returns for the threes (real estate, listed infrastructure and common listed equity) were determined using the following formula:

$$R_t = {}^{(EI_t - BI_t)}\!/_{BI_t} \text{ --------- } (4.10)$$

R_t represents return on asset class for month t, EI_t captures asset class index value at the end of month t and BI_t is the asset class index level at the beginning of month t. To ensure that all the variables were analyzed at the same frequency, monthly returns were converted into quarterly returns using the Eviews' high to low frequency conversion procedure. Unlisted infrastructure is provided on a quarterly basis, thus no need for any data transformation.

The real GDP growth rate and global Brent crude oil price returns were adopted as control variables. Both variables are likely to be significant in determining the performance of infrastructure investments in emerging markets. Babatunde (2017) argues that economic growth is negatively related to inflation whereas; the influence of oil prices on general price surge is inconclusive. The impacts of crude oil price fluctuations on general price increases are largely determined by the size and persistence of oil price changes and whether or not the nation in question is an oil exporter.

For panel data estimation approaches, the study used data from national stock markets in Brazil, China, India and Indonesia (on a monthly basis). These nations were picked solely considering the availability of specific stock market indices to the general public (especially infrastructure index). These were selected based on their ease of access to the public, researchers and investors. It is easy for investors to trade listed liquid securities during portfolio construction, diversification and portfolio revision than to obtain privately held equity (Paula, 2017). In a rational world, we expect listed and unlisted stocks to be valued based on the same fundamentals, not solely on whether or not the stock is publicly traded. Beta risk (broad market volatility) is expected to be insignificant and frequency of valuation (very high in listed stock) does not affect the business and financial risk of the firms in question, implying the same value for listed and unlisted stocks of similar firms.

Other variables used in panel data approach are defined as follows:

Inflation rate: Monthly consumer price index (CPI) changes per country were treated as a true representation of general price increases or surge in emerging economies.

Infrastructure sector returns: The following listed indices on infrastructure were adopted as proper representation of the infrastructure sector in developing economies - SSE 180 infrastructure index (China), Nifty infrastructure index (India), FTSE Brazil infrastructure extended total return (Brazil), and IDX Infrastructure index (Indonesia).

General listed equity returns: The study used the following indices to represent the general or composite listed equity returns in emerging markets - Shanghai Composite index (China), Bovespa index (Brazil), Nifty 500 (India) and FTSE Indonesia index (Indonesia).

Real estate returns: FTSE China A 600 Real estate investment and services (China), S&P BSE realty (India), IDX Property index (Indonesia), and Real estate index (Brazil), were applied as proxies of real estate returns in developing nations. All variables are expected to be positively related to asset returns implying that the asset class in question is a good inflation hedge.

In order to apply appropriate unit root and cointegration tests in panel data, there is need to confirm the incidence and non-appearance of cross-sectional dependence (CSD) among variables (Mallick *et al*., 2016; Onuoah, Okonkwo, Okoro, & Okere, 2018). To ensure validity of the results, the following four CSD tests were applied: Breusch-Pagan LM, Pesaran scaled LM, partiality-fixed scaled LM and Pesaran CD. Given the unbalanced nature of our data set as well as existence of CSD, most of the second and first generation unit root tests were incompatible. Therefore, the study adopted the Pesaran's Cross-Sectional Augmented Dickey-Fuller (PESCADF) which is a second generation unit root test, and Im-Pesaran-Shin (IPS) (a first generation stationarity test) tests to ascertain that all the variables under study are stationary in levels or after first differencing.

4.4. Data analysis and Results

This section outlines the general distribution and stochastic properties of the variables under study and the findings. The capacity of infrastructure and comparable asset classes to hedge inflation using linear and non-linear approaches is presented in ensuing sections.

4.4.1. Descriptive statistics for time series data

Table 4.1: Descriptive statistics

	crude oil	all stock	real estate	GDP	Inflation	listed infra	unlisted infra
Mean	0.565250	0.614000	0.403209	2.078904	0.383913	-0.168207	3.20625
Median	0.630000	0.620000	0.120530	2.021402	0.363681	0.720550	3.3375
Maximum	13.64000	10.47000	15.64010	3.778065	1.207361	31.02620	4.525
Minimum	-13.67000	-8.240000	-10.03360	-0.412187	-0.030972	-28.46030	0.575
Std. Dev.	5.295426	3.284050	3.971394	0.724128	0.204882	13.66650	0.8879
Skewness	-0.424780	0.060384	0.933680	-0.016148	1.543521	-0.094289	-1.4624
Kurtosis	3.691836	4.811539	7.539998	6.515456	8.118427	2.877138	5.23555
Jarque-Bera	2.000651	5.493764	40.16436	20.59912	59.54686	0.084428	22.58709
Prob	0.367760	0.064127	0.000000	0.000034	0.000000	0.958664	0.000012
Sum	22.61000	24.56000	16.12836	83.15618	15.35651	-6.728300	128.25
Sum Sq. Dev.	1093.620	420.6144	615.1068	20.45007	1.637085	7284.155	30.75174
Obs	40	40	40	40	40	40	40

Source: E-views computations using raw data

During the period under review, unlisted or private infrastructure equity fared better than all other assets, earning an average of 3.2 % per quarter. Listed infrastructure equity performed badly on average, realizing losses amounting to -0.168% which was well below average inflation during the period (0.384%), indicating that investors who invested in listed infrastructure investments during the period lost wealth (on average). Listed infrastructure exhibited violent swings in returns as indicated by the standard deviation amounting to 13.67. The notable differences between exchange traded and private infrastructure support the claim that exchange traded and unlisted infrastructure investments are complementary - they have different distribution and stochastic features. The notable differences between unlisted and listed infrastructure were also highlighted by Stack, (2014) and Langley (2016) giving suggestive evidence that the ability of these sub-categories of infrastructure markets to hedge inflation might also be different in emerging markets.

Real estate returns generally performed well, with an average return of 0.40 % per quarter. The same can be said of the general stock market index which on average earned 0.61%. The inflation rate was very low, averaging 0.384% every quarter. Even though investors are not expected to be wary of inflation risk under such an environment, drawing some insights and perspectives on the ability of infrastructure investments to combat inflation is still necessary. The minimum values of all the variables, save for unlisted infrastructure, were negative during the period under study, indicating that chances of losing wealth do exist in emerging markets. The average economic growth rate in emerging markets (measured by GDP) was positive during the period under study. This can be attributed to stable inflation environment which obtained during the period which made planning and budgeting easy and worthwhile. In general, the variables under study were not normally distributed as indicated by the excess kurtosis and corresponding Jarque-Bera probability values. Table 4.2 below presents the summaries of measures of moments for individual nations used in this study.

Table 4.2: Measures of moments for individual nations

Country	**Variable**	**Mean**	**Maximum**	**Minimum**	**Skewness**
Brazil	Infrastructure	0.00476	0.3239	-0.1761	0.743
	Inflation	0.00469	0.0132	-0.0023	0.481
	Composite stock	0.0092	0.1697	-0.1186	0.227
	Real estate	0.0133	0.5395	-0.1413	1.855
China	Infrastructure	0.0049	0.411	-0.238	1.629
	Inflation	0.00199	0.0158	-0.0113	0.371
	Composite stock	0.0063	0.2057	-0.2265	-0.127
	Real estate	0.0051	0.2646	-0.187	0.496
India	Infrastructure	0.00822	0.158	-0.093	0.205
	Inflation	0.00381	0.030	-0.00450	2.072
	Composite stock	0.0134	0.209	-0.114	0.464
	Real estate	0.0146	0.171	-0.163	-0.164
Indonesia	Infrastructure	0.00195	0.212	-0.124	0.552
	Inflation	0.00613	0.458	-0.0165	0.809
	Composite stock	0.013	0.3443	-0.1045	1.613
	Real estate	0.0074	0.793	-0.267	1.917

Source: Authors' compilation

In Brazil, the average monthly inflation rate stood at 0.47% below the returns generated by all the assets under considerations. Real estate investors generated high real returns on a monthly basis compared to investors in listed infrastructure and general listed stocks. The same applies to investors in India, real estate generated highest positive real returns relative to other assets under consideration. Investors in Indonesia with interests in infrastructure earned returns below the inflation rate on a monthly. Such negative real rate of returns gives indicative evidence of the incapability of infrastructure sector to hedge inflation. Average monthly returns from all assets were positively skewed save for real estate in India and general stock market returns in China. This might be due to the Chinese stock market crash of 2015 and trade war with the USA.

At panel data level, the stochastic distribution of the main variables used in this study is obtainable in Table 4.3, indicating the first, second, third and fourth moments of distribution:

Table 4.3: Stochastic distribution of the variables

	Real estate	**Infrastructure**	**Inflation**	**Composite stock**
Mean	0.013322	0.002402	0.004693	0.009225
Median	0.002300	-0.013900	0.004450	0.006250
Maximum	0.539500	0.323900	0.013200	0.169700
Minimum	-0.141300	-0.176100	-0.002300	-0.118600
Std. Dev.	0.091898	0.101188	0.002979	0.059611
Skewness	1.854655	0.767320	0.480941	0.227244
Kurtosis	10.61479	3.925341	3.488830	2.730134

Source: Authors' compilation

On average, the infrastructure sector in emerging markets earned below the inflation rate (0.2% against 0.4 %) on a monthly basis. On average, this left investors in infrastructure sector stocks worse off. It could be an indication of the diminished or constrained pricing power of the infrastructure sector in emerging markets. Composite stock returns and real estate earned returns above the average monthly inflation rate during the period under study, which is a favorable scenario as investors were able to protect their wealth from inflation. In a nutshell, the variables under study were positively skewed and exhibited moderate swings during the period.

4.4.2. Risk-adjusted return scores for time series data

The Sharpe quotient (which is a complete risk-adjusted return measure) and Sortino ratio (which is a downside risk-attuned return measure) were used in this study. The results are shown in Table 4.4 below taking note of the fact that the mean risk-free rate (Treasury Bill rate) during the 10 year term was 6.405% per annum in the emerging markets under study.

Table 4. 4: Individual asset risk-adjusted returns

Asset	**Sharpe ratio**	**Sortino ratio**
Unlisted infrastructure	1.9345	3.2207
Listed infrastructure	-0.12426	-0.1805
Real estate	-0.28224	-0.37038
EM equity	-0.27631	-0.39192

Source: Authors' extract from Microsoft Excel computations

As can be drawn from the table, unlisted infrastructure stocks earned above all other assets under review. On both ratios, unlisted infrastructure proved to be an investment to reckon with as it earned way above inflation and risk free rate. The difference between exchange traded and private (unlisted) infrastructure returns really boggles the mind of rational economic man assuming that markets are informationally efficient.

4.4.3. Multi-collinearity results for time series data

The level of bivariate correlations amongst the variables under study is displayed in Table 4.5 below:

Table 4.5: Bivariate correlations results

	crude oil	all stock	real estate	GDP	Inflation	listed infra	unlisted infra
crude oil	1.000000						
all stock	0.505863	1.000000					
real estate	0.321628	0.801820	1.000000				
GDP	-0.072765	-0.134224	-0.223439	1.000000			
Inflation	0.236834	0.221372	0.075781	0.048182	1.000000		
listed infra	0.336487	0.423324	0.348592	0.030984	0.065327	1.000000	
unlisted infra	-0.323125	-0.506105	-0.323840	0.134911	0.025320	-0.267151	1.000000

Source: Eviews 10 bivariate correlations computations

Considering the correlation coefficients above, it is of interest that all the variables are positively related to inflation, although the magnitude differs. This might be an indication of the hedging abilities of the asset classes under consideration. As confirmation of the claim that exchange traded and private infrastructure investments are complementary, the correlation coefficient between them is negative (-0.267). The correlation between unlisted infrastructure and other assets is negative indicating that unlisted infrastructure investments exist in a class of their own.

Listed infrastructure is positively related to all variables except unlisted infrastructure. This implies that listed infrastructure does not possess defensive investment features as it fails to oppose the general market trends. This is against the claim that investors can draw some diversification benefits by including listed infrastructure in their portfolios.

Another surprising feature is the existence of an inverse link between GDP and real estate and general equity market yields (captured as all stock). This is not expected in efficient markets where stock markets developments are expected to mirror the economy. The behavior noted in this study is normally associated with the use of stock markets as a gambling platform or as a hedge when all other investment avenues are no longer viable or closed. In other words, the stock market will experience higher trading volumes in tight economic situations as investors shun real economic activity and try to realize returns from equity trading. Another possible reason for this negative relationship is the existence of a significant number of unlisted firms such as small to medium enterprises, which are a key feature of emerging markets. This being the case, only a handful of companies (not a true representative of the economy) are listed on local bourses. As a result, the stock market does not mirror the economy.

The bivariate correlation measurements of the key variables using panel data are given in the Table 4.6 below:

Table 4.6: Correlation matrix using panel data

	Real estate	Infrastructure	Inflation	Composite stock
Real estate	1.000000			
Infrastructure	0.755833	1.000000		
Inflation	-0.015859	-0.160669	1.000000	
Composite stock	0.779660	0.883822	-0.174369	1.000000

Source: Authors' compilation

Inflation is negatively correlated with all the asset categories under study. This suggestively upholds the proxy hypothesis and the 'inflation illusion' in emerging markets. In other words, an increase in inflation is treated as a negative signal as far as economic prospects are concerned and risk averse investors tend to offload their stock portfolios, leading to a fall in stock returns. The infrastructure sector is positively related to real estate and composite stock, which indicates co-movement in the same direction over time. This implies that the shocks which affect stock markets sweep across all sectors in a similar way in emerging markets.

4.4.4. Cross-sectional dependence (CSD) tests for panel data

To determine the applicability of second generation stationarity detection, the study applied CSD assessments and the outcomes are shown in Table 4.7. Four approaches were used to ensure validity of the results (see Appendices 57-62).

Table 4.7: Cross-sectional dependence test statistics

Variable	**Breusch-Pagan LM**	**Pesaran scaled LM**	**Bias-corrected scaled LM**	**Pesaran CD**
Infrastructure	276.00	77.9422	77.8978	16.6132
Inflation	756.00	216.5064	216.4904	27.4954
Real estate	487.00	189.209	172.081	18.306
Composite stock	756.00	216.5064	216.4904	27.4954
GDP	756.00	216.5064	216.4904	27.4954
Crude oil	756.00	216.5064	216.4904	27.4954

Source: Extracts from Eviews

All the statistical values were significant at 99% confidence interval, indicating the manifestation of sectional dependence in all the variables under study. This could be due to particular issues pertaining to the BRICS (Brazil, Russia, India, China and South Africa) economic partnership from which three units of study (Brazil, China and India) were drawn. Economic policies, regulatory measures, trading trends and the growth rates of the BRICS nations tend to co-move; hence, the manifestation of CSD.

4.4.5. Unit root tests for time series data

To validate the use of ARDL and NARDL models, the study applied four unit root and stationarity tests (refer to Appendices 1-28). The results thereof are shown in Table 4.8 below:

Table 4.8: Stationarity tests results

Variable	**ADF**	**PP**	**KPSS**	**Ng-Perron**
Crude oil price	I(0)	I(1)	I(1)	I(0)
All stock	I(1)	I(1)	I(0)	I(1)
Real estate	I(0)	I(1)	I(1)	I(0)
GDP	I(1)	I(0)	I(0)	I(1)

Inflation	I(0)	I(1)	I(1)	I(0)
Listed infrastructure	I(1)	I(0)	I(1)	I(1)
Unlisted infrastructure	I(1)	I(1)	I(0)	I(1)

Source: Eviews 10 model estimation output

The above results show none of the variables applied in this present research were integrated of order two or higher, substantiating the use of the ARDL approach. The empirical model adopted in this study is applicable when all the variables are stationary in levels or after first differencing; otherwise, the results will be biased (Nkoro & Uko, 2016). It should be noted that no single unit root or stationarity test is without flaws; hence, the use of four tests to validate the results. For example, Ely and Robinson (1997) argue that, the ADF test can potentially be influenced by low power and thus outcomes might be distorted in finite samples. On the same note, some stationarity tests possibly will give unfair outcomes when the data sample is small (Baum, 2004). To address this problem, this study applied four unit root tests, including the Ng-Perron stationarity test that gives more dependable and reliable outcomes. ADF, Philips Perron, Ng-Perron and KPSS tests results indicated that all the variables applied in this research are stationary in levels and after first differencing, substantiating the use of the ARDL model (See Appendices 1-28).

4.4.6. Unit root tests for panel data

Pesaran's cross-sectional augmented Dickey-Fuller (PESCADF) together with Im-Pesaran-Shin (IPS) checks of stationarity were engaged to validate the integration levels of the variables under study (see Appendices 63-74). The outcomes are shown in Table 4.9 hereunder.

Table 4.9: Unit root tests results

Variable	**PESCADF**	**IPS**	**Level of integration**
Infrastructure	-3.873	-7.916	Order 1
Inflation	-4.629	-9.7612	Oder 1
Real estate	-2.581	-6.052	In levels
Composite stock	-2.893	-18.453	In levels
GDP	-3.942	-7.435	Order 1
Crude oil	-5.924	-12.983	In level

Source: Authors' compilation

As clearly indicated in Table 4.9 above, none of the variables is integrated of order greater than 1. This indicates the appropriateness of the PARDL approach. These levels of integration might have been affected by structural breaks such as the European sovereign debt crisis of 2009, Chinese stock market crash of 2015 and arguably the global financial crisis of 2007/8 as some authorities claim that the crises ended in June 2009 in some economies like USA (NBER, 2010).

4.4.7. Parameter estimation using ARDL approach

As noted earlier, for comparison purposes, four models were estimated alternating the asset classes as dependent variables regressed by actual inflation, whereas GDP and crude oil price were treated as control variables. The optimum lag intervals were ascertained using the Akaike Information Criteria (AIC) and the lags were not the same across variables and models.

4.4.7.1. Model 1 –unlisted infrastructure inflation hedging ability

Using the unlisted infrastructure assets as the dependent variable, ARDL (3,1,4,4) was the best model. The results for the model are presented in Table 4.10 hereunder:

Table 4.10: Inflation hedging ability of unlisted infrastructure

Short run				**Long run**		
Response variable	Coefficient	p-value		Response variable	coefficient	p-value
D(unlistedinfra(-1))	0.2115	0.0514		Inflation	237.07	0.0932
D(unlistedinfra(-2))	0.5034	0.0003		Gdp	55.766	0.5022
D(inflation)	4.9869	0.925		Oilprice	-0.5215	0.000
D(gdp)	35.57	0.2893				
D(gdp(-1))	-67.937	0.0587				
D(gdp(-2))	-118.108	0.0020		**F-Bounds tests**		
D(gdp(-3))	-205.342	0.000		F-statistic	10.33	
D(oilprice)	0.0671	0.0286				
D(oilprice(-1))	0.304	0.000				
D(oilprice(-2))	0.1789	0.002				
D(oilprice(-3))	0.05766	0.0717				
EC term	-0.7232	0.000				

Source: Author’s compilations from ARDL estimates

The 'D' on the response variable stands for differenced variable and the number in the parenthesis indicates the lag order.

On short term basis, the inflation coefficient is positive and insignificant, indicating that unlisted infrastructure is a poor inflation hedge (see Appendix 30). Such results are not surprising given that inflation-asset return relationship is premised on Fisher (1930) long run equilibrium model. The inability of unlisted infrastructure to withstand inflation shocks in the short term is expected cognizant of the murky pricing process in private equity markets. The results concur with Sawant (2010) who noted insignificant positive coefficients, as well as Wurstbauer and Schaufers (2015). The error correction term indicates the existence of long run relationship between the variables under study. This is supported by the F-bounds test result.

In the long run, unlisted infrastructure investments hedge inflation at 10% level of significance (see Appendix 29). This concurs with the argument that adjustments for inflation take time and are not instantaneously passed on to stock prices. The illiquid and long-term nature of infrastructure private equity might be another reason for this long-run relationship as it takes time before the private equities market responds to inflation shocks. These results are in tandem with those of Wurstbauer and Schaufers (2015) who used US data and noted that infrastructure asset returns can act as a hedge against inflation in the long term. However, they are contrary to those of Bird *et al.* (2014) and Peng & Newell (2007) who concluded that infrastructure assets are poor at hedging inflation.

4.4.7.2. Model 2 – listed infrastructure inflation hedging ability

With listed infrastructure as the dependent variable, the parsimonious model was ARDL (5,4,2,5) and the results are shown in Table 4.11 below.

Table 4.11: Inflation hedging ability of listed infrastructure

Short run				**Long run**		
Response variable	Coefficient	p-value		Response variable	coefficient	p-value
D(listedinfra(-1))	0.5977	0.018		Inflation	-1824.926	0.4619
D(listedinfra(-1))	0.59596	0.03		Gdp	-93.2424	0.8068
D(listedinfra(-1))	1.1448	0.00		Oil price	8.1456	0.4178
D(listedinfra(-1))	1.1706	0.00				
D(inflation)	-20.29	0.064		**F-bounds tests**		

D(inflation(-1))	0.354	0.973		F-statistic	4.7698	
D(inflation(-1))	35.82	0.005				
D(inflation(-1))	16.486	0.112				
D(gdp)	1.5078	0.831				
D(gdp(-1))	-7.389	0.093				
D(oilprice)	1.737	0.005				
D(oilprice(-1))	-0.662	0.388				
D(oilprice(-1))	-2.114	0.008				
D(oilprice(-1))	-1.860	0.005				
D(oilprice(-1))	-0.889	0.043				
EC term	-1.425	0.000				

Source: Author's compilations from ARDL estimates

The 'D' on the response variable stands for differenced variable and the number in the parenthesis indicates the lag order.

For listed infrastructure, the current quarter inflation rate negatively and significantly affects infrastructure investments at 10%, in agreement with Peng and Newell (2007). This supports Fama's proxy hypothesis that indicates that stocks are a perverse inflation hedge. Immediate past quarter inflation cannot be hedged using listed infrastructure investments.

Interestingly, listed infrastructure investments can hedge inflation realized in the past two quarters at 5% level of significance, indicating the lengthy process required for information to impact stock market prices and the long-run feature of infrastructure green field projects (see Appendix 36). Given that the inflation rates were generally low during the period under study, it is expected that firms were not very wary of inflation risk, hence took their time to adjust asset prices in line with inflation developments. The same can be said on stock market investors. The coefficient is significantly above unit, indicating that listed infrastructure is more than a perfect hedge and supporting the Fama-Schwert model. The noted inflation hedging ability of listed infrastructure is contrary to the findings of Rodel and Rothballer (2012) who concluded that listed infrastructure is a poor inflation shield. The F-bounds test in line with the error correction term testify the existence of long –run relationship between the variables in emerging markets

On long term basis, listed infrastructure was found to be negatively related to general price surge, although insignificant (see Appendix 36). This is in agreement with the findings of Peng and Newell (2007), and Martin (2010). However, the results contradict Wurstbauer (2015) who concluded that infrastructure investments can be used effectively as inflation hedges on long term basis.

4.4.7.3. Model 3 –real estate inflation hedging capacity

ARDL (4,0,5,0) was the optimal model when real estate was treated as the dependent variable. The results displayed in Table 4.12 below indicated absence of short-term link between real estate and inflation rate.

Table 4.12: Inflation hedging ability of real estate

Short run				**Long run**		
Response variable	Coefficient	p-value		Response variable	coefficient	p-value
D(realestate(-1))	0.478	0.103		Inflation	90.264	0.622
D(realestate(-2))	0.477	0.031		Gdp	-0.583	0.996
D(realestate(-3))	0.335	0.023		Oilprice	0.0326	0.676
D(gdp)	-2.078	0.299				
D(gdp(-1))	2.722	0.039		**F-bounds tests**		
D(gdp(-2))	2.989	0.009		F-statistic	3.312	
D(gdp(-3))	-0.746	0.496				
D(gdp(-4))	-2.763	0.029				
EC term	-1.458	0.000				

Source: Author's compilations from ARDL estimates

This is expected given the long-run nature of most real estate projects and investments. This incapability of real estate to act as an inflation hedge on short term phase concurs with the findings of Zhang (2013) and Di (2012) using data from China (see Appendix 42). In the long run, real property returns are positively linked with general price surge rates in emerging economies (see Appendix 41). However, the relationship is not significant, indicating that real property is a poor inflation hedge. This is contrary to findings of Lee (2014), and Wu and Tidwell (2014).

4.4.7.4. Model 4 –general stock returns inflation hedging capacity

In the short run, listed stocks in emerging markets are not a hedge against inflation (see Table 4.13 below (Appendix 48).

Table 4.13: Inflation hedging ability of general stock returns

Short run				**Long run**		
Response variable	coefficient	p-value		Response variable	coefficient	p-value
D(gdp)	-3.24	0.021		Inflation	250.079	0.138
D(gdp(-1))	1.195	0.153		Gdp	-60.597	0.531
D(gdp(-1))	3.307	0.000		Oilprice	0.143	0.051
D(gdp(-1))	1.131	0.192				
D(gdp(-1))	-2.109	0.012		**F-Bounds tests**		
EC term	-1.166	0.000		F-statistic	11.99	

Source: Author's compilations from ARDL estimates

This supports the findings of Phiri (2016) in relation to the Johannesburg Stock Exchange, and Tripathi and Kumar (2014). However, the results contradict those of Eita (2012) and the Fama-Schwert (1977) model. In the long run, listed common stocks exhibited a positive and insignificant relationship with inflation which is in agreement with Sawant (2010) (see Appendix 47).

In a nutshell, at 10% level of significance, unlisted infrastructure exhibited inflation hedging capabilities on long term basis. At 10% level of significance, listed infrastructure investments proved to be a perverse inflation hedge of current inflation. In contrast, listed infrastructure more than perfectly hedged inflation realized in the past two quarters at 5% level of significance. In other words, current listed infrastructure returns hedge inflation recorded two quarters ago. On short and long term basis, real estate and general common listed stock are poor inflation shock shields. To conserve space and brevity, diagnostic tests (normality, autocorrelation, heteroscedasticity and stability tests) are not displayed and the results indicated that the models were properly specified and stable (see Appendices 31-34, 37-40, 43-46 and 49-52).

4.4.8. Parameter estimation using NARDL model

As four assets were under investigation, each was separately assessed and the results were captured under four models to assess asymmetric inflation hedging ability. Each model addresses a single asset's ability to hedge asymmetric inflation shocks. The optimum number of lags included in each model was specified using the Akaike Information Criteria (AIC).

4.4.8.1. Model 1 - asymmetric inflation hedging ability of unlisted infrastructure

The first model evaluated the hedging capabilities of unlisted infrastructure. The estimates from Model 1 are shown hereunder in Table 4.14 below.

Table 4.14: Model 1 estimates (unlisted infrastructure as the dependent variable)

Short-run effects				**Long-run effects**		
Ind. variable	Coefficient	p-value				
EC term	-0.3072	0.003			Coefficient	P-value
InflP(-1)	-0.753	0.736		Inflation +	-2.451	0.739
inflN(-1)	-0.6346	0.777		Inflation -	2.066	0.779
D(inflP)	1.7866	0.259				
D(inflP(-1))	1.8484	0.468				
			Tests			
		F-statistics	p-value			F-statistics
asymmetry	short-run	5.746	0.024	Cointegration	F-pss	3.7804
	long-run	0.2963	0.591		T-bdm	-3.2306

Source: Authors’ extracts from Stata 13

From the table above, the only significant coefficient worth noting is the short-run asymmetry, indicating that in the short run, positive and negative changes to inflation poses a dissimilar effect on private or unlisted infrastructure investments (see Appendix 53). Unlisted infrastructure investments failed to exhibit any significant capacity to hedge either positive or negative inflation shocks, both on short and long term basis which is contrary to Wurstbauer and Shafers (2015:19-44). Although the effects are not significant, the impact of positive changes in inflation is negatively related to unlisted infrastructure investments’ performance (-2.451) in the long run. Negative shocks to inflation lead to positive changes in unlisted infrastructure investments’ performance. The long-term link between unlisted infrastructure and general price increases was established by the existence of a significant error correction term given that the F-test results are inconclusive.

4.4.8.2 Model 2 - asymmetric inflation shielding capability of listed infrastructure

The outcomes from the evaluation of asymmetric general price increase protection capability of listed infrastructure yields are displayed in Table 4.15 below.

Table 4.15: Model 2 coefficient estimation results (listed infrastructure as the dependent variable)

Independent Variable	**Short-run coefficient**	p-value			**Long-run effects**	
EC term	-1.188	0.001			Coefficient	P-value
inflaP(-1)	-13.0392	0.742		Inflation +	-10.975	0.742
inflaN(-1)	-14.308	0.715		Inflation -	12.043	0.714
D(inflp)	-4.756	0.849				
D(inflp(-1))	-5.986	0.873				
D(inflp(-2))	37.858	0.245				
D(inflp(-3))	-27.976	0.301				
D(infln)	-30.2638	0.296				
D(infln(-1))	-20.6236	0.516				
D(infln(-2))	-14.767	0.519				
D(infln(-3))	9.038	0.566				
			Tests			
	Asymmetry	F-statistics	p-value		Cointegration	F-statistics
	short-run	0.9783	0.336		F-pss	5.0168
	long-run	0.1655	0.689		T-bdm	-3.83

Source: Authors' extract from Stata 13

The impact of negative and positive inflation shocks is mixed on short term basis (positive and negative) though insignificant (see Appendix 54). On the long term basis, the effects are the same as those for unlisted infrastructure. It must be emphasized that all the coefficients are insignificant save for correction towards a long-run relationship. These results propose that, exchange traded infrastructure securities are not effective hedges against general price increases and that the impact of inflation on listed infrastructure is symmetrical on short and long term basis. The findings are in tandem with those obtained by Peng & Newell (2007) and Bird *et al.* (2014).

4.4.8.3. Model 3 - asymmetric inflation shielding capacity of real property

The asymmetric general price increase protection capability of real estate was examined for comparison purposes and the findings thereof are displayed in Table 4.16.

Table 4.16: Model 3 estimation results (real property as the dependent variable)

Short-run coefficients				Long-run effects		
Ind. variable	Coefficient	p-value				
EC term	-1.41675	0.035			Coefficient	P-value
inflaP(-1)	-0.667	0.939		Inflation +	-0.471	0.94
inflaN(-1)	-0.938	0.913		Inflation -	0.663	0.915
D(inflp)	-0.3839	0.49				
D(inflp(-1))	9.249	0.297				
D(infln)	7.5445	0.256				
D(infln(-1))	-0.4251	0.925				
Tests					Tests	
	Asymmetry	F-statistics	p-value		Cointegration	F-statistics
	short-run	0.0192	0.891		F-pss	2.2618
	long-run	0.1209	0.731		T-bdm	-2.2618

Source: Authors' extracts from Stata

The results indicate the absence of asymmetry on short and long term basis (see Appendix 55). Like listed infrastructure, in emerging markets, real property sector yields cannot effectively protect investors from general price increase on short and long term basis. These findings are however in disharmony with the Fama and Schwert model of 1977.

4.4.8.4 Model 4 - asymmetric inflation hedging capability of general equity

The results from the final model where the general listed stock in emerging markets was treated as the asset of interest are displayed in Table 4.17.

Table 4.17: Model 4 estimates (general equity as the dependent variable)

short run coefficients				long run effects		
Ind. variable	coefficient	p-value				
EC term	-1.0103	0.00			Coefficient	P-value
inflaP(-1)	1.0897	0.844		Inflation +	0.041	0.842
inflaN(-1)	1.401	0.802		Inflation -	-1.387	0.798
D(inflp)	-1.714	0.635				
D(inflp(-1))	5.94	0.302				
D(infln)	10.796	0.022				
D(infln(-1))	-4.224	0.222				
			Tests			
	Asymmetry	F-statistics	p-value		Cointegration	F-statistics

	short-run	0.0825	0.776		F-pss	8.968
	long-run	0.509	0.482		T-bdm	-4.769

Source: Authors' extracts from Stata

Although a long-run relationship was noted between general listed equity and inflation, general equity failed to hedge inflation partial sums (see Appendix 56).

In summary, the existence of short- and long-term asymmetry was noted between unlisted infrastructure and decomposed inflation. Other asset classes indicated the existence of symmetric impacts on short and long term basis. From all the four models, the impact of long-run positive and negative inflation jolts on the respective asset returns was positive and negative, respectively (though insignificant). Diagnostics tests are displayed for each model as per appendices referred above. The models were stable, with normally distributed errors and constant variance.

4.4.9. Parameter estimation using the PARDL model

This section presents the coefficients obtained from the three estimators in evaluating the general price increase defensive capacity of infrastructure, real property and general equity returns in emerging markets. The parsimonious model specified by the Akaike information criterion was PARDL (1.1) model in all three cases - infrastructure, real estate and general equity. Individual countries' short-term parameters estimated from the application of PMG estimator are shown in Table 4.18 below (ignoring control variables and constant to conserve space).

Table 4.18: PMG individual nation short-run results

	Asset class	**Infrastructure**		**Real estate**		**Composite stock**	
Nation	Ind. variable	Coefficient	p-value	coefficient	p-value	Coefficient	p-value
Brazil	ec term	-0.8328	0.00	-0.9236	0.00	-0.94	0.00
	D(inflation)	-0.1017	0.064	-0.0210	0.463	-0.031	0.112
China	ec term	-0.939	0.00	-0.917	0.00	-0.886	0.00
	D(inflation)	-0.0116	0.312	-0.0214	0.084	-0.011	0.231
India	ec term	-1.0266	0.00	-0.9267	0.00	-0.998	0.00
	D(inflation)	0.010	0.171	0.01077	0.34	0.0039	0.263
Indonesia	ec term	-0.923	0.00	-0.864	0.00	-0.93	0.00
	D(inflation)	0.0082	0.299	-0.0084	0.472	0.0009	0.921

Source: Extracts from PMG estimation

From Table 4.18 above, it is noticeable that a significant long-term connection was found among the variables for all four nations as evidenced by less than zero and significant error correction terms (see Appendices 75-77). At 10% level of significance (which is very high for inferences in general), the inverse association between infrastructure sector and general price shocks is significant for Brazil. All other coefficients are not significant. This supports the “proxy hypothesis” where an increase in inflation is treated as an indicator that firms will face bleak and uncertain future prospects and hence, decreased firm value as well as equity values. The existence of an inverse connection between inflation and equity yields was also noted by Tripathi & Kumar (2014).

All other coefficients are insignificant, indicating the inability of different asset classes to hedge inflation on short term basis. Such findings are in agreement with the outcomes gotten by; Bitsch *et al.* *(*2010), Sawant (2010), Bird *et al*. (2014) and who found insignificant coefficients between inflation and infrastructure in the US and Australia. Given that the generalized Fisher equilibrium hypothesis (where the Fama-Schwert model is derived) is a long-term relationship, the results are not surprising.

4.4.9.1. Infrastructure sector’s inflation hedging ability

The results derived from the assessment of the infrastructure sector’s ability to hedge inflation using three estimators in emerging markets are presented in Table 4.19. The short-run coefficients from PMG are excluded as they were shown at individual nation level in Table 4.18 above. The model derived from Equation 4.8 treating infrastructure as the dependent variable is as follows:

$$\begin{aligned}\Delta \text{Infrastructure}_{it} & \\ &= (\varphi_i \text{Infrastructure}_{i,t-1} + \beta'_{1i} inflation_{it} + \beta'_{2i} GDP_{it} + \beta'_{3i} crude_{it}) \\ &+ \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta \text{Infrastructure}_{i,t-j} \\ &+ \sum_{j=0}^{q-1} \delta^{*\prime}_{1ij} \Delta inflation_{i,t-j} + \sum_{j=0}^{q-1} \delta^{*\prime}_{2ij} \Delta GDP_{i,t-j} + \sum_{j=0}^{q-1} \delta^{*\prime}_{3ij} \Delta crude_{i,t-j} + \mu_i + \varepsilon_{it} \\ &- - - (3)\end{aligned}$$

where in this case $\delta^{*\prime}_{1ij}$ indicates the extent to which infrastructure hedges inflation in emerging markets in the short run.

Table 4.19: Infrastructure sector and inflation hedging

	Estimator	MG		DFE		PMG	
	Response variable	coefficient	p-value	coefficient	p-value	coefficient	p-value
Long Run	Inflation(-1)	-0.00431	0.387	-0.01098	0.197	-0.00999	0.151
	GDP(-1)	0.0077	0.131	-0.00046	0.933	0.00128	0.825
	Crude oil(-1)	0.18633	0.122	0.1291	0.039	0.0799	0.13
Short Run	ec term	-0.947	0.00	-0.941	0.00		
	D(inflation)	-0.0.1914	0.389	-0.00014	0.983		
	D(GDP)	-0.0033	0.811	0.00772	0.464		
	D(crude oil)	0.0332	0.322	0.02871	0.549		
	Constant	0.00333	0.061	0.0091	0.311		

Source: Extracted from model estimations

Using all three estimators, the link between inflation and infrastructure sector yields is inconsequential on short term and long term basis (refer to Appendices 75-83). This indicates the sector's inability to withstand general price increase shocks in developing economies on long and short term basis. The findings are in line with estimates obtained using PMG model as specified in Table 4.18 above. These results concur with those obtained by Rodel & Rothballer, (2012), but are contrary to Colonial First State's (2009) findings. Crude oil price changes were found to be significant (under DFE only) in predicting infrastructure returns in the long run. This is expected given the role played by crude oil in the infrastructure sector in emerging markets in the production and provision of many goods and services. As indicated by the negative and significant error terms from all estimators, long-run relationships exist between infrastructure sector returns and inflation, GDP and crude oil prices in emerging markets.

4.4.9.2. Real estate inflation hedging capacity

The results on real estate's capability to hedge inflation shocks in developing are presented in Table 4.20. Short-run coefficients from the PMG estimator are excluded from as they were presented in Table 4.18 above. Like infrastructure sector returns, real estate returns in emerging markets are poor at hedging inflation on long and short term basis, which concurs well with Ibrahim and Agbaje's (2013) findings.

Table 4.20: Real estate inflation hedging ability

	Estimator	MG		DFE		PMG	
	Response variable	Coefficient	p-value	coefficient	p-value	Coefficient	p-value
Long Run	Inflation(-1)	-0.0116	0.299	-0.0018	0.838	-0.0082	0.432
	GDP (-1)	0.01385	0.129	0.0116	0.049	0.00733	0.199
	Crude oil(-1)	0.0204	0.649	0.0437	0.363	0.0361	0.622
Short Run	EC term	-0.9354	0.00	-0.924	0.00		
	D(inflation)	-0.0117	0.239	0.00286	0.71		
	D(GDP)	0.0185	0.314	0.0403	0.00		
	D(crude oil)	-0.0335	0.125	-0.019	0.747		
	Constant	-0.0051	0.743	-0.0034	0.708		

Source: Authors' compilation

GDP was found to be positive and significant in determining real estate returns using DFE in the long run, which is acceptable given the non-defensive long term nature of real estate assets (refer to Appendices 75-83). All other coefficients were not significant except for the error correction terms that exhibited the existence of long term link among real estate yields and GDP, and crude oil prices.

4.4.9.3. General listed stock's ability to hedge inflation

Turning to composite stocks' capacity to hedge inflation in developing economies, the results are displayed in Table 4.21 below:

Table 4.4: Composite stock inflation hedging capacity

	Estimator	MG		DFE		PMG	
	Response variable	Coefficient	p-value	coefficient	p-value	coefficient	p-value
Long Run	Inflation(-1)	-0.0113	0.141	-0.0043	0.497	-0.0038	0.313
	GDP (-1)	0.0071	0.139	0.00384	0.252	0.0037	0.081
	Crude oil(-1)	0.12	0.007	0.137	0.005	0.1198	0.011
	ec term	-0.967	0.00	-0.930	0.00		

Short Run	D(inflation)	-0.0118	0.233	-0.00005	0.992
	D(GDP)	0.0097	0.243	0.01456	0.005
	D(crude oil)	0.0468	0.189	0.055	0.134
	Constant	0.0022	0.737	0.0056	0.310

Source: Extracts from model estimation

The insignificant coefficients from the three estimators suggest that listed common stock in emerging markets is not effective in hedging inflation. These findings contradict those of Incekara *et al.* (2012) and Emenike and Nwankwegu (2013) in the Nigerian market. Only crude oil was positive and significant on long term basis using DFE and MG as well as GDP applying DFE (refer to Appendices 75-83). This is expected given the indispensable role of crude oil in emerging nations and the logic that stock markets tend to mirror economic developments.

The results from the three estimators (MG, DFE and PMG) indicate the inability of the infrastructure sector, real estate and general equity to withstand actual inflation in emerging markets on short and long term phases. Thus, investing in listed stocks on emerging stock markets cannot provide investors with immunity against inflation.

The lack of inflation hedging capacity arises due to multiple reasons. It might indicate firms' inability to adjust their prices in line with inflation developments. Consequently, their pricing power might be questionable. This is expected given government intervention in the economic activities of emerging nations. For example, 23.8% of Brazil´s CPI basket is made up of charges fixed by the regime. In most cases, the regulated prices are either way above or way below the inflation level. The same can be said of Indonesia where electricity and energy prices are set by the government. Given the bureaucratic nature of emerging nations, price changes by national governments take a long time to take effect (if they do at all) and are almost always below the inflation rate. As a result, stock returns from firms or sectors exposed to government intervention cannot hedge inflation in the short or long run.

Informational inefficiency might also be a reason for stock returns' inability to hedge inflation (Carlson, 2020). The capital markets might be inefficient in incorporating pricing power into stock returns (if firms do indeed have such power). Stock's failure to hedge inflation could also be attributed to the existence of massive debt in the capital structure (which is profound in infrastructure firms). When inflation increases, so does the cost of servicing old and new debt. Thus, even if organizations are capable of raising charges in tandem with obtaining inflation, the effect of increased debt obligations might offset that of increased earnings on stock value. Furthermore, during inflationary periods, consumption patterns are normally negatively affected as the purchasing power of salaries, savings and wealth in general is eroded. Decreased aggregate demand leads to lower sales volume. This implies that even if firms can increase prices in line with inflation, reduced sales volume off-sets this advantage, leading to lower cash-flows to stockholders.

On the same note, the inflation illusion might be significant among financial market participants in emerging markets, with investors discounting the positive impact of inflation on nominal earnings and simultaneously compounding the negative effect of inflation on current values. Subsequently, stock prices decrease as inflation increases, leading to a negative relationship. The inflation illusion is compounded by the existence of irrational investors and noise traders in the market. Such investors and analysts barely consider fundamentals when valuing and trading stocks, and simply follow the crowd (herd behavior).

4.5. Conclusions and Recommendations

The study assessed the degree up-to which infrastructure securities can protect investors from the ravaging effects of inflation in emerging markets (from 2009 to 2019). The ARDL, NARDL and PARDL approaches were adopted to expose both long- and short-run interactions between asset returns and inflation.

Using the ARDL model, the results indicated that listed infrastructure acts in harmony with both the Fama-Schwert model (hedges inflation) and Fama's proxy hypothesis (is a perverse inflation hedge) on short term basis (at 10% level of significance). Unlisted infrastructure investments proved to be an effective inflation hedge on long term basis at 10% level of significance. Results also indicated that listed infrastructure is a poor inflation hedge even at 10%. This substantiates the claim that listed and unlisted infrastructure investments complement each other and can thus be part of the same portfolio and effectively diminish inflation risk affecting the portfolio. Real estate and common listed equity exhibited a lack of inflation hedging capabilities in emerging markets from 2009 to 2018. Thus, it was concluded that infrastructure hedges inflation better than real estate and general listed stocks in emerging markets (at 10% level of significance).

Utilizing the NARDL approach, the findings indicated that infrastructure investments (listed or unlisted) in emerging markets are not asymmetric inflation hedges. Restated, it is a myth to claim that infrastructure investments hedge inflation in emerging markets. The same can be said of real estate and general listed equity. In the short run, unlisted infrastructure exhibited an asymmetric response, implying that it responded in a different way to negative and positive inflation adjustments. In all the other asymmetric tests, the results were insignificant (although all long-run coefficient signs indicated some asymmetries). Significant long-term link was noted between general price increase and all the assets under consideration save for real estate.

The study also adopted a PARDL approach using MG, DFE and PMG estimators in the verification of the short-term and long-term inflation protection capacity of infrastructure, real property and composite stocks in emerging markets. The results were insignificant in all cases, implying that the assets considered in this study are poor inflation hedges.

In summary, findings from this study (using ARDL,NARDL and PARDL) confirm the inability of the infrastructure sector, real property and composite equities to withstand inflation shocks on short and long term periods (at 5% level of significance). This signposts the presence of significant beta risk in emerging stock markets, implying that when the market is heading north or south, all listed stocks follows suit (no sacred cows). Investors do not gain immunity to inflation by investing in the infrastructure segment of the economy in developing markets. As such, financial marketplace participants should consider commodities, currencies and metals as alternatives in their quest to hedge inflation. It should be emphasized that no asset can hedge inflation under all scenarios. Portfolio revision is paramount when inflation trends are changing.

The different stochastic and distributional properties of exchange traded and private infrastructure securities imply that investors and portfolio managers can realize some risk diversification benefits by holding exchange traded and private infrastructure securities in the same portfolio. On a similar note, active portfolio management is recommended as the response of the assets that were considered to inflation shocks changes as the investment horizon stretches from short to long terms. Given that assets' capacity to hedge inflation differs with time horizons and inflation rates, portfolio revision is necessary.

It should be noted that during the period under study, very low levels of inflation were the norm in emerging markets under study. Hence, the results should be treated with caution. On the same note, the indices used covered specific sub-sectors of infrastructure (energy, social transportation, utilities, and telecommunication). Cognizance should be taken of the fact that different assets, act as inflation hedges at different inflation levels. It must be emphasized that, when it comes to hedging inflation, not only the inflation rate, but also the holding period matter. As indicated in this study, no single asset can hedge inflation at short- and long-run. Therefore, portfolio revision is of paramount importance as the investment horizon changes from short to long holding periods. In other words, passively managing a portfolio does not guarantee a hedge to inflation.

On the same note, given that the infrastructure sector is still in its infancy in developing nations, investors should keep up to date on regulatory changes which might affect the sector's pricing power. The infrastructure sector is broad and diverse; thus, considering sub-sectors like transport and energy might be profitable for investors in emerging markets. Investors need to be cautious given that regulatory regimes are dynamic and that previously monopolistic infrastructure firms might lose their edge as well as their pricing powers (Swedroe, 2013). This is especially significant in emerging markets where economic liberalization is on the rise. Investors should thus be aware that, due to high debt levels in the capital structure of most infrastructure firms, rising inflation might also mean increased debt premiums which could leave equity owners worse off or in the same position (before the rise in inflation). In other words, if infrastructure firms refinance their operations with inflation linked debt, their ability to hedge inflation might be under threat.

This study refutes the claim that listed and unlisted infrastructure is a single asset using methodologies which can extract both short and long term interactions. This was evidenced by different distributional features of listed and unlisted infrastructure which was further substantiated by differences in inflation hedging abilities of listed and unlisted infrastructure.

This study used better methodologies instead of simply comparing the inflation rates and infrastructure returns as is the norm in industrial bulletins. On the same note, the paper transposed a proper academic model used in evaluating inflation risk hedging capability of commodities and assets like gold, real property and currencies. The paper therefore makes significant input to the body of knowledge in terms of geographical area covered, decomposing infrastructure asset and applying proper models.

The present study makes significant contributions in terms of methodology (non-linear models), asset class under consideration (infrastructure) and geographical coverage (emerging markets). Past studies used linear models, concentrated on general equity and gold's ability to hedge inflation in developed nations. The study made deeper analysis as the estimators used enabled individual country analysis on the investment feature under study.

Future researches could decompose real inflation into estimated and unpredicted inflation and assess the infrastructure sector's ability to hedge the same. Research could also be steered covering the inflation protection capacity of this sector under different inflation regimes (creeping, galloping and hyper-inflation). Given the heterogeneous nature of the infrastructure sector, assessing the inflation hedging capacity of sub-categories (telecommunication, energy) could also be fruitful. In light of the heterogeneous nature of emerging economies in terms of political risks, economic development and regulatory frameworks, future studies could conduct individual country analysis. Unfortunately, very little data is available on infrastructure returns in individual nations.

CHAPTER 5

MODELING AND FORECASTING INFRASTRUCTURE SECTOR RETURNS VOLATILITY BEHAVIOR IN EMERGING MARKETS

5.1.0. Chapter introduction

Although the volatility aspect (measured using standard deviation) was highlighted in previous papers, this present paper went a step further in properly addressing the volatility structures of infrastructure investments in developing economies. Infrastructure is claimed to be associated with less volatile returns as one of its intrinsic investment features. As such, this paper aims to refute or accept this claim in comparison with other asset classes. In this paper only listed infrastructure was used given that the generalized autoregressive conditional heteroscedasticity (GARCH) group of approaches adopted in this study are appropriate for high frequency data like daily data and not quarterly or yearly frequencies available for unlisted infrastructure.

Status of the paper- published in the Eurasian Journal of Business and Economics (EJBE).

Abstract

Understanding the volatility behavior of specific sectors of the economy enables investors to formulate workable investment strategies, and policy-makers to come up with policies that dampen excess volatility. This study examined the volatility features of the infrastructure sector in emerging markets. The features assessed were the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) effects, volatility persistence and leverage effects. EGARCH and GJR-GARCH models of order one under normal and non-normal error distributions were employed to unpack the volatility behavior of infrastructure, real estate and general equity returns in emerging markets. The results from both models under all distributions indicated the existence of GARCH effects, volatility clustering, volatility persistence and leverage effects in the infrastructure sector in emerging nations. This implies that past conditional variance is significant in determining current conditional variance, thereby rendering forecasting a worthwhile task. The findings also suggest that investors interested in the infrastructure sector in emerging markets should incorporate leverage effects in their estimation of value-at-risk (otherwise the value will be underestimated). Furthermore, they should focus on factors other than

mean-variance portfolio optimization and consider leverage effects, excess kurtosis and skewness when making investment decisions. Finally, investors in the infrastructure sector in emerging markets are encouraged to formulate hedging strategies as they are exposed to significant risk and uncertainty.

5.1.1. Paper introduction

Volatility of financial markets is becoming increasingly important to investors and policy makers especially after the international financial crises of 2007/8. Understanding the volatility behavior of financial markets assists policy makers to design regulations to dampen the effects of such behavior on domestic financial markets (Uyaebo, Atoi, & Farida, 2015). As a crude measure of risk and economic stability as well as investor sentiments, volatility performs an influential part in capital marketplaces when it comes to management of risk (value at risk computations), option pricing, allocation of assets and management of portfolios (Pati, Barai & Rajib, 2018; John & Amudha, 2019).

Volatility of financial markets is an important issue in emerging economies when financial markets are exposed to violent external shocks and domestic upheaval resulting from political and economic factors (Wilson, Ugwuanyi, & Nwaocha, 2019). Forecasting and modeling volatility in emerging markets is thus crucial, not only for international investors but all economic agents as it affects real economic activities, company investment and capital structure decisions, consumer spending and saving patterns, portfolio revisions and the performance of stock markets (Rahahleh & Kao, 2018). Mashamba & Magweva (2019) noted that high volatility in financial markets makes raising long term capital very costly and difficult and ultimately results in misallocation of resources. Volatile markets erode investor confidence and make financial assets unattractive due to erratic and wild price movements (Wilson *et al.,* 2019; Islam, 2013).

However, volatility is a double-edged sword as extremely volatile assets and securities like crypto-currencies, foreign currency and listed shares record abnormal returns in the short run. As such, investors need to know how to model and predict volatility so that they benefit from (or at least hedge) market swings.

Risk averse investors are in constant search of assets and investments which produce less volatile and steady returns. Given its claimed financial and economic characteristics, the infrastructure sector is one such investment (Thompson, 2019). The sector also enjoys monopolistic and oligopolistic powers (pricing powers), inelastic demand (for products) and inflation linked price adjustments (from concessions and agreements). It is defensive and less responsive to economic and business cycles as it provides products that are the backbone of any economy and are rarely substitutable (Burke, 2017).

Consequently, the infrastructure sector's returns and stock prices are expected to be stable and less volatile than those in other economic sectors.

However, deregulation of this sector is gaining momentum and, given its political importance, government interference in pricing is likely. Furthermore, volatility in stock markets is not only driven by fiscal and financial rudiments (such as changes in the monetary policy and earning power) but also by irrationality and behavioral traits and biases (such as overconfidence and over-reaction to negative news) among investors and fund managers (Statman, 2018). This could result in the infrastructure sector exhibiting similar risk-return features to those in other sectors.

Wurstbauer and Schafers (2015) and Finkenzeller (2012) note that few academic studies have been conducted on the infrastructure sector in general, and particularly on volatility features in emerging markets. Publications by investment professionals and companies have employed basic statistical approaches (like standard deviation and mean return) to analyse the risk-return profile of this sector. Moreover, most of these studies have been confined to developed nations. The current study sought to fill these methodological and geographical gaps.

The study investigated the volatility features of the infrastructure sector in emerging nations where industrialization, urbanization, and population growth, coupled with economic growth, have heightened demand for infrastructure. Emerging markets are in critical need of infrastructure investment. Indeed, the World Bank (2018a) notes that demand outstrips supply to the tune of USD 1.3 trillion per annum. Given the political uprising and violent destruction of property in emerging economies, the gap is likely to be bigger than the stated amount. Empirical investigation of the volatility features of infrastructure investments in emerging markets is of crucial importance to fund managers and policy architects as they design investment policies and formulate infrastructure concessions in an attempt to spur infrastructure provision and reduce the ever-growing gap in emerging economies (Mashamba & Magweva, 2019).

The volatility features scrutinized in this present research included volatility persistence (tenacity), volatility clustering (bundling) as well as leverage effects. Persistence in volatility indicates the degree to which a shock on the variable under study lasts (Uyaebo *et al.*, 2015). For example, if a variable exhibits momentous volatility tenacity, this entails that once a jolt is introduced on the variable, it will take extended periods to expire or to decay. In other words, the variable will swing up and down for an elongated tenor, which is undesirable for investors, consumers and policy makers. The opposite is true for variables with low volatility persistence, which is desirable for investors and economic growth as it makes planning and forecasting easier.

Leverage effects imply a non-linear rejoinder of conditional variance (volatility) to changes or shocks by the variable under study. The existence of leverage effects indicates the existence of the fact that the effect of negative information on future conditional variance or volatility is bigger relative to the effect of positive information of equivalent degree (Owidi & Mugo-Waweru, 2016). In other words, the future volatility of the variable's responses depends more on negative than positive shocks, implying an inverse link between current variable changes and future variable volatility or risk. Transposed to market returns, volatility or conditional variance rises more rapidly when returns are decreasing than when they are increasing (Aydemir, Gallmeyer, & Hollifield, 2006). Value-at-risk computations must be adjusted for the presence of leverage effects; otherwise, the value will be underestimated (Engle, 2004). In the same vein, stock market investors require a premium as compensation for uncertainty if leverage effects are exhibited.

Reverse volatility asymmetry arises when positive news (increased returns) impacts more than negative news (a fall in returns) on future conditional volatility generated by the variable under study (like equity returns). Absence of leverage effects and reverse volatility asymmetry indicates the existence of an equal reaction to positive and negative news – with the matching and equal effect on conditional variance (Wan, Cheng & Yang, 2014).

The rest of this research paper is arranged in the following manner: the second unit highlights the key concepts and attributes of the infrastructure sector, while section three converses the procedures and methods adopted in the study. Section four presents and discusses the findings, and section five provides an overall conclusion and recommendations to investors and policy makers.

5.2. Literature review

As noted earlier, there is a paucity of academic research on the infrastructure sector, let alone on the phenomenon of volatility in emerging nations. Blanc-Brude (2015) noted that infrastructure sector returns are less volatile than those in other sectors as demand for its products and services is inelastic and less responsive to economic and business cycles. Firms operating in this sector provide utilities and essential services which in most cases have no readily available substitutes. The infrastructure sector thus enjoys pricing powers which can be manipulated to protect its earning power in the short and long run. Moss (2014) noted that the sector is characterized by monopolistic or oligopolistic features, inelastic demand, predictable and stable cash inflows, high operating margins, and a long asset life. Given that this information is publicly available, we would expect that infrastructure sector stocks would earn steady, less volatile returns, assuming informationally efficient financial markets.

However, the deregulation drive in most emerging markets is undermining the pricing powers of the infrastructure sector (Swedroe, 2013). At the same time, infrastructure sector stocks might deviate from their fundamental value due to investor irrationality and the existence of inefficient capital markets. Consequently, stock returns might be just as volatile and unsteady as other assets like listed stocks and bonds.

Bahceci and Weisdorf’s (2014) empirical study on infrastructure cash flows in the US and Western Europe noted that such assets are less volatile than traditional assets. Kempler (2016) and Babson (2013) employed global indices to show that listed infrastructure exhibited lower volatility than global property, and global common equity.

However, to the finest of the researchers’ acquaintance, no empirical research has been published on the volatility aspects of the infrastructure sector in both developing and developed nations. The current study is thus a pioneer one on infrastructure sector volatility behaviour in emerging markets.

Previous studies on stock markets in general (not specific to infrastructure) indicated the existence (and absence) of leverage effects and volatility persistence. Table 5.1 below presents a snapshot of such studies.

Table 5.1: Snapshot of studies on stock market volatility

Author(s)	**Nation(s)**	**Conclusions**
Banumathy and Azhagaiah (2015); John and Amudha (2019)	India	Weighty leverage effects were found
Yeh and Lee (2000)	China	Reverse volatility asymmetry noted
Jingli and Sheng (2011); Hou (2013)	China	Leverage effects were exhibited
Mashamba and Magweva (2019)	Southern Africa	Leverage effects and volatility asymmetry were established
Okpara and Nwezeaku (2009)	Nigeria	Less volatility persistence and leverage effects
Guidi (2008)	Europe	Significant leverage effects were found
Kalyanaraman (2014)	Saudi Arabia	Volatility clustering, persistence noted
Dana (2016)	Amman	Symmetric response

Source: Authors’ compilation

While the current study focused on the infrastructure sector, the results of past studies on different stock markets suggested the results and conclusions that could be expected.

5.3. Methodology

This segment outlines the tests as well as the models used to examine the volatility behaviour of infrastructure sector returns relative to other asset classes in emerging nations.

5.3.1. Empirical model

In establishing the volatility behavior of the infrastructure sector in emerging economies, the study adopted the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) as well as Glosten-Jagannathan and Runkle (GJR) GARCH (equivalent to Threshold GARCH) first order models (1,1) using normal and non-normal error distributions namely, Student's T, as well as generalized error distribution (GED). Mashamba & Magweva (2019) and Ekong & Onye (2017) note that GARCH approach miss the mark on accounting for all leptokurtosis in the data if the conditional variance is not normally distributed, thereby rendering the approach inefficient.

Most common models of volatility/variance assume that volatility is constant over time (Fabozzi, Focardi, Rachev, & Arshanapalli, 2014). Empirically, this assumption has been disputed. High frequency financial data is usually heteroskedastic, often exhibiting volatility bundling, excess kurtosis and leverage effects (Ekong & Onye, 2017). This invalidates the use of linear models in volatility estimation (Banumathy & Azhagaiah, 2015). As such, volatility is now commonly appraised by means of GARCH specification and its variants. The GARCH approach propounded by Bollerslev (1986) was extended from an ARCH model (attributed to Engle, 1982) which stipulates that volatility tends to be time variant and clustered, especially in equity market data.

When estimating the ARCH family models, the leading step is to confirm mean reversion presence or absence through the application of various unit root tests and graphical presentation (John & Amudha, 2019). The second procedure involves estimating the best fitting conditional mean equation (Dana, 2016). The conditional mean equation follows an Auto-Regressive Moving Average (ARMA) specification expressed as follows:

$$R_t = \beta R_{t-1} + \varepsilon_t + \lambda \varepsilon_{t-1} --------- (5.1)$$

where R_t captures infrastructure (real estate and general stock market) sector returns whereas ε denotes usual residual term. The Akaike information criterion (AIC) was used to ascertain the proper lag length to use in the mean equation using the *'varsoc'* command in Stata 13.

After estimation of the mean equation; the manifestation of 'ARCH effects' is tested. The existence of 'ARCH effects' calls for the econometric use of ARCH family models (John & Amudha 2019), while the absence of such effects in the residuals renders an ARCH approach worthless and wrongly specified.

The application of the ARCH specifications is legitimized by the incidence of serial correlation of variance or heteroscedasticity, volatility clustering, leptokurtosis, and non-normality of returns.

Under the ARCH approach the conditional volatility, σ_t^2, is dependent on lagged amount of the squared error (u). Thus:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 ---------- (5.2)$$

Considering the GARCH (1,1) specification, which is widely employed, the conditional variance or volatility is determined by own lags and the lagged squared error terms (u). This is structured in the following manner:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 -------- (5.3)$$

The weakness of the GARCH model hinges on its assumption of symmetry, implying that positive (good newsflash) and negative jolts (bad newsflash) exert an equal impact on conditional variance in the model (Ekong & Onye, 2017). To counter this, Nelson (1991) proposed the EGARCH (1,1) approach which was adopted in this research. As specified by Coffie (2015), the EGARCH (1,1) specification is structured in the following way:

$$log(\sigma_t^2) = \alpha_0 + \beta_1 \, log(\sigma_{t-1}^2) + \alpha_1 \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \lambda_1 \frac{u_{t-1}}{\sigma_{t-1}} ----- (5.4)$$

where (σ_t^2) denotes variance at time t, and u captures the error term, whereas, α and β are experiential coefficients estimated using the maximum likelihood approach. The α parameter captures the size impact or the symmetric impact of the model, the “GARCH” effect. The volatility persistence of shocks is captured using parameter β under the EGARCH model. The parameter λ captures the impact of news of future volatility of the infrastructure sector. If λ is negative and significant (where $\lambda_1 < 0$), it designates the presence of leverage effects. If above zero and momentous ($\lambda_1 > 0$), it point to the existence of reverse volatility asymmetry. The effect is symmetric if $\lambda_1 = 0$.

The GJR-GARCH (similar to the TGARCH model) was one more asymmetric GARCH specification adopted in this research. The model is specified in the following way:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \, u_{t-1}^2 + \beta \, \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} ----- (5.5)$$

where, I_{t-1} represents the dummy variable assuming the codes 0 and 1. The dummy variable will be equivalent to 1 if u_{t-1}^2 is not more than 0 (negative shocks) and 0 otherwise. In the case that parameter γ is above zero and momentous, leverage effects exist.

5.3.3. Forecasting methods

The dynamic forecasting method was used to appraise the predicting ability of the adopted approaches. More specifically, mean squared errors (MSE), as well as the root mean square error (RMSE) loss functions were used in this study. The MSE, which penalizes big estimate errors more sternly relative to other communal accuracy tests, is determined as follows:

$$MSE = \sum_{t}^{n} \frac{e_t^2}{n} - - - - - - - - - (5.6)$$

In which case $e_t = \mathrm{y}_t - \hat{\mathrm{y}}_t$ where y_t denotes actual value observed in period *t* whereas $\hat{\mathrm{y}}_t$ is the fitted value in period *t* and *n* captures the sample size.

The RMSE, which is favored by academics and practitioners, is expressed as follows:

$$RMSE = \sqrt{\sum_{t}^{n} \frac{e_t^2}{n}} - - - - - - - - (5.7)$$

The lesser the measure of these loss functions, the greater the forecasting efficiency of the model or approach under consideration.

5.3.2. Data and data source

This empirical study used the Standard and Poor Emerging Markets Infrastructure Daily Total Return Index as a proxy for infrastructure sectors in emerging markets from 1 July 2009 to 1 July 2019 (2 605 observations). The total return index comprises interest, dividends and other allocations like rights issues, realized over a period of time. It is the new benchmark when it comes to evaluating the earning power of mutual funds and portfolio managers at large (Blanc-Brude, 2019).

The following formula was used to convert the daily total return index into daily continuously compounded yields (in percentages):

$$R_t = ln(P_t|P_{t-1}) * 100 - - - - - - - - (5.8)$$

where P_t and P_{t-1} are the end of day index on day *t* and *t-1* correspondingly, and R_t is infrastructure sector (as well as real estate and general stock market) return on day *t*.

5.4. Results and findings

This part display and discusses the outcomes attained using the above models on the volatility features of the infrastructure sector, real estate and general stock markets returns in emerging markets.

5.4.1. Preliminary analysis

The distributional features, including first; second, third and fourth moments of the three asset in emerging nations are presented in Table 5.2 below.

Table 5.2: Measures of moments

	Mean	Max	Min	Std. dev	Skewness	Kurtosis	J-B	Prob
Infrastructure	0.0181	5.4538	-6.434	0.9573	-0.3587	6.4975	1383	0.000
Real estate	0.004	0.076	-0.134	0.0168	-0.0695	5.69	756	0.000
General equity	0.015	5.5185	-6.7	0.9652	-0.24	6.028	979	0.000

Source: Extract from E-views

On average, infrastructure sector stock investors earned 0.0181% daily. The Jarque-Bera probability is significant at 1%, indicating non-normal distribution of infrastructure stock returns in emerging markets. Evidence of heteroscedasticity is exhibited by the existence of excess kurtosis (6.4975, which is bigger than 3). As indicated by the skewness value (-0.3587), the returns were negatively skewed during the period under study. Same distributional features are also evident for real estate and general equity returns.

5.4.2. Stationarity tests

To ascertain the order of integration, the study applied three unit root (and stationarity) tests to validate the results. The outcomes are displayed in Table 5.3 below. For brevity and to conserve space, infrastructure unit root test results are displayed (refer to Chapter 6 and Appendices 84-92 for full results).

Table 5.3: Stationarity tests outcomes for infrastructure

	T-statistic	Decision
ADF	-42.192	Stationary in levels - I(0)
Phillips-Perron	-41.794	Stationary in levels - I(0)
KPSS	0.1034	Stationary in levels - I(0)

Source: Authors' extracts from Eviews

The Augmented Dickey-Fuller (ADF) (which is grounded on parametric transformation), the Phillips-Perron (PP) (which is a non-parametric test that addresses the autocorrelation in the residual term) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, all attest to the stationarity in levels of infrastructure sector daily stock returns in developing economies. These outcomes are in tandem with the financial literature that specifies that stock returns tend to be stationary in levels as the returns are effectively derivatives of stock prices (normally integrated of order one). Real estate and general equity returns also exhibited stationarity in levels (results not presented for brevity).

5.4.3. 'ARCH' effects test

In validating the use of the ARCH family models, the study tested for the occurrence of 'ARCH effects' using graphical and statistical methods. Volatility bundling is clearly exhibited in Figure 5.1 below as phases of large volatility or swings are followed by phases of large swings, and phases of small volatility are followed by phases of low volatility.

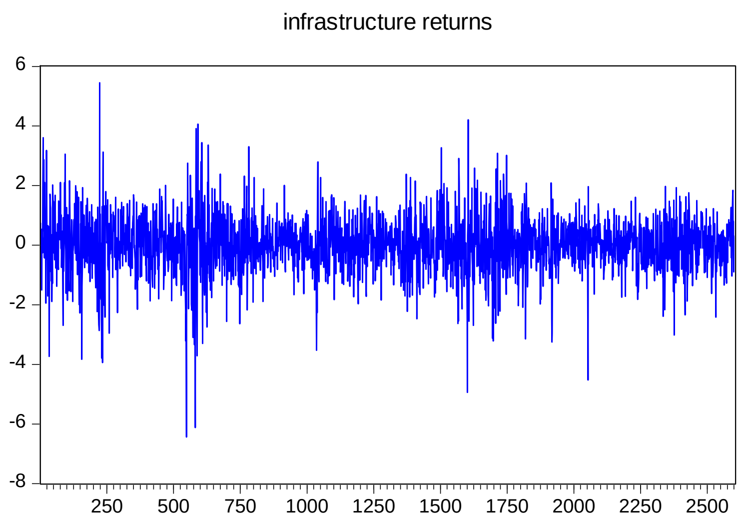

Figure 5.1*: Volatility bundling of infrastructure*

It is evident from Fig 5.1 that variance is not constant (refer to Chapter 6 for other asset classes). Excess kurtosis, skewness and non-normality of the returns (see Table 5.2 above) all point to the validity of the ARCH models.

To formally ascertain the presence of ARCH effects, the ARCH LM test was used on the errors from the mean equations and the results are shown in Table 5.4 below. Parsimonious mean equations (ARMA) were of order 4 for infrastructure and real estate and of order 3 for general stock market.

Table 5.4: Heteroscedasticity Test: ARCH LM test

Asset	F-statistic	Prob.ChiSquare
Listed infrastructure	44.03218	0.0000
Real estate	54.03871	0.0003
General equity	34.72104	0.0000

Source: Authors' extract from Eviews

It can be safely concluded that the errors are not homoscedastic, thereby further validating the appropriateness of the GARCH family of models on all three assets under review.

5.4.4 EGARCH and GJR-GARCH specification estimation results

This section outlines the results obtained from estimating the EGARCH and GJR-GARCH specifications of order 1. The results of the variance equation for infrastructure sector returns (dependent variable) employing the EGARCH (1,1) model using three error distributions are summarized and presented in Table 5.5 below.

Table 5.5: EGARCH (1,1) estimation results for infrastructure

Parameter (response variable)	Normal	Student's T	GED
C (constant)	-0.09992	-0.07938	-0.08957
α (garch effects)	0.11999	0.09473	0.10685
λ (leverage effects)	-0.07122	-0.06298	-0.06545
B (volatility persistence)	0.97656	0.98319	0.98022

Source: Authors' extract from Eviews

Considering all the error distributions, the coefficients are momentous at 1% level of significance (refer to Appendices 96-98). The same is true for real estate and general equity market returns in developing economies (results for the two assets not presented here for brevity and due to space constraint, (refer to Appendices 93-95 and 99-101). The GARCH effects are above zero and substantial in emerging markets' infrastructure sector returns, implying that past volatility is significant in predicting current volatility (variance is auto-correlated). Emerging markets' infrastructure sector returns have a significant response to the absolute size of the shock. This is in harmony with Kalyanaraman (2014) and Mashamba & Magweva (2019), who noted the existence of GARCH effects in Saudi Arabian and Southern African stock markets, respectively.

The level of volatility persistence is very high (0.97656) and significant, indicating that once a shock is introduced to the infrastructure sector in emerging markets, it requires long periods to decay - it possess a lengthy memory. This persistence is normally attributed to market inefficiency (whereby information is slowly assimilated and captured in stock prices) and the momentum effect - which is a behavioral bias. Financial market participants, particularly risk averse investors, respond irrationally to any piece of information that purports to erode the value of their investments (Wilson *et al.*, 2019).

The large number of investors (local and foreign) in emerging markets implies different market analysis methods, as well as different beliefs and forecasts strategies. Such variation stimulates 'noise' in the marketplace, accentuating volatility tenacity as heterogeneous investors and fund managers (including necromancers) capture news in stock prices (Mashamba & Magweva, 2019).

The leverage effect coefficient is below zero (-0.07122) and substantial, indicating the existence of an asymmetric rejoinder to bad and good (positive) news by investors in emerging markets' infrastructure sector. An inverse link exists between past yields and current conditional variance in the infrastructure sector in emerging markets. Restated, the impact of negative information or shocks on forthcoming volatility is superior to the influence of positive information of the equivalent size. This is contrary to the conclusions reached by Dana's (2016) study considering Amman stock market, Oskooe & Shamsaravi's (2011) research on Iran's stock market and Niyitegeka & Tewari's (2013) analysis of South African equity exchange, which noted the absence of asymmetric effects**.**

The results from the GJR-GARCH assuming different distributions are shown in Table 5.6 below (refer to Appendices 102-104).

Table 5.6: GJR-GARCH (1,1) estimation results for infrastructure

Parameter (response variable)	**Normal**	**Student's T**	**GED**
C (constant)	0.04571	0.01998	0.0216
arch term	0.03617	0.02432	0.0251
λ (leverage effects)	0.11879	0.07146	0.0774
garch term	0.84658	0.91379	0.9079

Source: Authors' extract from Eviews

The above outcomes are in line with those obtained using the EGARCH model; i.e., significant volatility persistence, leverage effect, ARCH term and GARCH term (at 1% level of significance). They concur with John & Amudha (2019) and Coffie (2015), although these authors did not specifically examine the infrastructure sector. However, they contradict the conclusions reached by Saleem (2007) and Aliyu (2011) who detailed the presence of reverse asymmetric volatility. As for general emerging stock market returns, ‘ARCH’ effects were absent using the three error distributions meaning that past residual sizes do not significantly affect current volatility. Real estate also indicated the absence of leverage effects under normal error distribution thereby implying symmetrical response of current volatility to positive and negative shocks of same size (refer to Appendices 108-110 and Chapter 6). Absence of ‘ARCH’ effects was also noted under the GED.

The existence of significant volatility persistence in emerging markets’ infrastructure stock returns implies that shocks on the sector takes time to die out, thus making volatility predictions worthwhile (refer to Appendices 105-107 and Chapter 6). This might be of assistance to investors, firms and money managers interested in making hedging and speculating decisions on volatility in the infrastructure sector in emerging markets.

However, stock market investors tend to demand a higher risk premium in the face of volatility persistence. This translates into higher costs of capital, high bid-ask spreads and increased costs of providing liquidity, all leading to depressed private and foreign direct capital injections in the infrastructure segment in developing economies (Emenike, 2010). Infrastructure firms operating in emerging markets are negatively affected by the existence of volatility persistence as they require significant reserves of cash and liquid assets in an attempt to reassure creditors and other stakeholders of their permanence and reliability (Ndwiga & Muriu, 2016). Consequently, the value attached to firms in the infrastructure sector in emerging markets is comparatively lower than those in stable and efficient financial environments. Stock market development is threatened when significant volatility persistence is exhibited, although abnormal returns can be earned.

The existence of leverage effects was notable in both models, implying that stock market participants in the infrastructure sector tend to over-react to deleterious information or developments and under-react to affirmative information. In other words, volatility responds more to undesirable shocks than optimistic shocks of the matching proportions. The leverage effect is attributable to ‘noisy’ uninformed and irrational investors in such markets (Avramov, Chordia, Jostova, & Philipov, 2007). The fact that the leverage effects and GARCH effects are both significant entails that as the asymmetric effect of shock is accounted for, the absolute magnitude of the shock is equally vital.

Similar results were obtained from the real estate and general listed stock returns volatility features. This means that all the assets under consideration are prone to same volatility issues, refuting the claim that infrastructure investments are less volatile than real estate and common listed stocks.

5.4.5. Forecasting ability of models

For brevity, forecasting results for infrastructure were presented. Results from other asset classes are just highlighted narratively. After ascertaining the diagnostic stability and appropriateness of both models, dynamic forecasts were performed and the results thereof are presented in this section. The loss function values from the EGARCH forecasts are displayed in Table 5.7 below (refer to Appendices 114-116).

Table 5.7: EGARCH loss function values

Loss function	Normal	Student's T	GED
RMSE	0.9572	0.9572	0.95713
MAE	0.7020	0.7015	0.70149

Source: Authors' compilation

The distribution providing the best forecast under the EGARCH model is the GED. The loss function results from GJR GARCH specification are shown in Table 5.8 hereunder (refer to Appendices 111-113):

Table 5.8: GJR-GARCH model loss function values

Loss function	Normal	Student's T	GED
RMSE	0.9570	0.9570	0.9564
MAE	0.7014	0.7011	0.7006

Source: Authors' compilation

The GJR-GARCH model executes best under the GED in comparison to other distributions. This is in tandem with the results obtained from the EGARCH forecasts. From the forecasts made, the GJR-GARCH specification performs better relative to EGARCH model in all error distributional assumptions. This is based on slightly lower loss function values from the GJR-GARCH model compared to EGARCH with slightly higher loss function values. Similar findings were obtaining considering real estate and general stock returns in emerging markets (refer to Appendices 117-128 and Chapter 6).

5.5. Conclusion and Recommendations

Understanding the dynamic volatility behavior of infrastructure sector returns in emerging markets is paramount in the face of the ever-increasing infrastructure deficit and financial market instability.

Comprehending the volatility behavior of specific sectors of the economy enables investors to formulate workable investment strategies and policy-makers to design policies that dampen excess volatility. This research study laid bare the volatility features of the infrastructure segment in emerging markets. The stylized features assessed were the GARCH effects, volatility persistence and leverage effects. This study used EGARCH and GJR-GARCH specifications of order one under normal and non-normal error distributions to unpack the volatility behavior of infrastructure returns in emerging markets. GJR-GARCH model is superior to EGARCH approach in modeling and forecasting infrastructure yields in emerging markets.

The results from both models under all distributions indicated the existence of GARCH effects, volatility bundling, and volatility tenacity and leverage effects in the infrastructure sector, real estate and general listed stocks in emerging nations. They imply that past conditional variance is significant in determining current conditional variance, thereby making forecasting a worthwhile undertaking. The existence of volatility bunching means that phases of big (small) volatility or swings are alternated by phases of big (small) volatility in the infrastructure sector in emerging markets. Once introduced into the financial market, volatility from the infrastructure sector takes time to decay. The effect of deleterious news on forthcoming conditional volatility is superior to that of optimistic news. This asymmetric behavior is amplified by the existence of irrational and uninformed traders who overact to negative news and underreact to positive news.

The exhibited volatility features imply that investors interested in the infrastructure (and real estate and general listed stocks) sector in emerging markets should incorporate leverage effects in their estimation of value-at-risk (otherwise the value will be underestimated). It is also recommended that investors go beyond mean-variance portfolio optimization and consider leverage effects, excess kurtosis and skewness when making investment decisions. Investors in the infrastructure segment in developing markets should also formulate hedging strategies as they are exposed to significant risk and uncertainty.

Corporates in the infrastructure and real property segment in developing economies should be willing to absorb an additional risk cost as lenders are exposed to significant volatility persistence, an illiquid sector and increased anxiety. It is recommended that financial regulators in emerging markets should formulate policies which address the identified volatility features. On the same note, policy makers should try by all means to reduce negative news emanating from policy inconsistencies, macro-economic instability and political instability. The regulatory authorities are encouraged to design policies which promote a well-functioning, stable financial environment to spur economic growth. Otherwise, investors will require a risk premium, increasing the cost of capital and hampering the availability of long term capital, thereby dampening nations' economic growth prospects. To add on, the exhibited volatility persistence negatively affects investment decisions and undermines the price stability role of monetary authorities thereby affecting economic growth. As such, regulatory authorities are recommended to formulate policies and economic environment with instill investor confidence and dampens financial market volatility.

Given the heterogeneous nature of emerging markets, further research could include country-by-country analysis. In-depth sub-sector analysis could also offer significant insights into volatility behavior in the infrastructure sector in emerging markets. As data becomes increasingly available, evaluating the volatility features of unlisted infrastructure might provide useful insights and conclusions.

This paper made valuable contributions to the existing body of knowledge. This paper went further and beyond the elementary measure of volatility- namely standard deviation- in evaluating the volatility aspects of infrastructure, real estate and general equity returns providing room for comparative analysis. This paper evaluated the effect of positive and negative shocks of listed infrastructure on future volatility or risk using robust GARCH family models of volatility. On the same methodological contribution, this paper used asymmetry GARCH models using three set of error distributions thereby promoting model efficiency. Establishing the proper volatility model (GJR-GARCH using GED) aids in investment analysis, risk management (in the calculation of Value at Risk) and portfolio revision.

This study provides insights into volatility (risk) features of exchange traded infrastructure sector returns in emerging markets. In other words it is a pioneer study covering infrastructure volatility features in emerging markets, thereby providing a basis for future studies to anchor on. On the same note, the paper confirms the existence of common volatility features in infrastructure, and real estate sectors in emerging markets. Therefore this paper confirms (or establishes) a rule of thumb which stipulates that listed assets in emerging markets are homogenous.

Valuable insights and implications to institutional investors and policy makers provide a valuable contribution on how investors should manage risk and what to expect when raising funds in emerging markets. Thus, the paper provided applicable recommendations for investors and policy makers in their attempt to promote economic stability and attract private investment

The study refutes the claim that exchange traded infrastructure securities offer less volatile returns relative to real estate and general stock returns in developing economies. In other words, the study upholds the proposition that exchange traded securities is susceptible to similar stylized volatility features.

CHAPTER 6

FURTHER ANALYSIS OF SPECIFIC PAPERS

6.0. Introduction

Most journals provide a limit as to the number of words, tables and pages in a single paper (5000 to 6500 words). Resultantly, some of the above outlined papers, in line with specific journal requirements, removed some tables and tests which might be necessary in fully explaining the significance of infrastructure investment features in emerging markets. As such, this chapter is actually part of the articles presented in Chapters 3-5. This chapter specifically outlines such important tests and analysis for Paper.

Chapter 5 paper: Modeling and forecasting infrastructure sector returns volatility behavior in emerging markets.

6.1.0 Results and Discussion

This segment of the chapter highlights the results not fully addressed in the main paper stated above.

6.1.1 Unit root tests

Stationarity tests for real estate and general equity returns in emerging markets were made, using three common tests. The outcomes are shown in Table 6.1 hereunder (refer to Appendices 84-89):

Table 6.1: Stationarity tests results

	Real estate		**General equity returns**	
Test type	T-statistic	Integration level	T-statistic	Integration level
ADF	-47.872	I(0)	-40.948	I(0)
Phillips-Perron	-47.839	I(0)	-40.332	I(0)
KPSS	0.1602	I(0)	0.0325	I(0)

Source: Author’s extracts from Eviews

As the two assets were stationary in levels, no transformation was made to the original data set.

The application of the GARCH family of models is premised on the existence of stylized facts like volatility clustering and excess kurtosis. The graphical illustration of volatility clustering for the two assets is shown in Figs 6.1 and 6.2 hereunder:

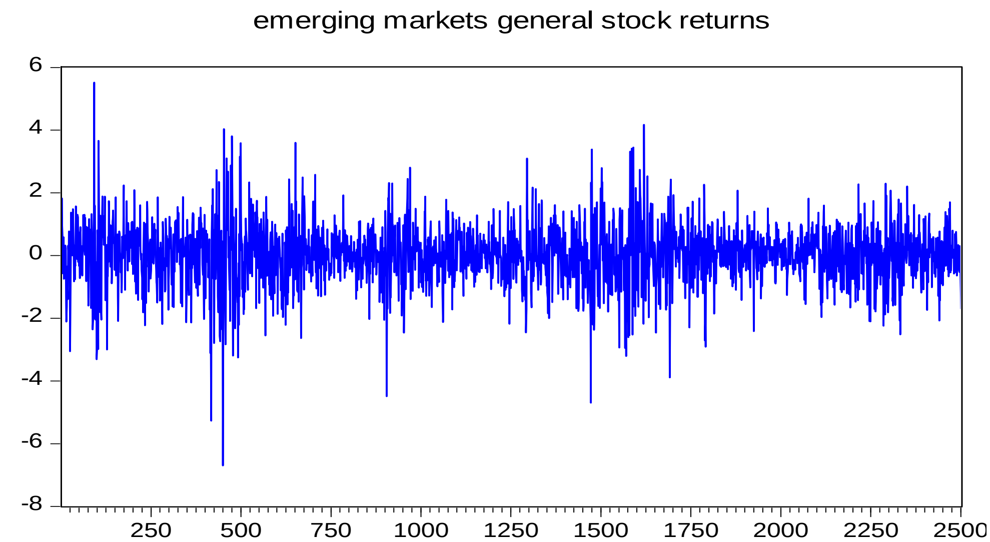

Figure 6.1: Volatility bundling of general stock returns

As evident from the figures, moments of great volatility are shadowed by subsequent violent swings and moments of calmness (small volatility) are shadowed by moments of small volatility. Interestingly, these bouts of volatility seem to alternate.

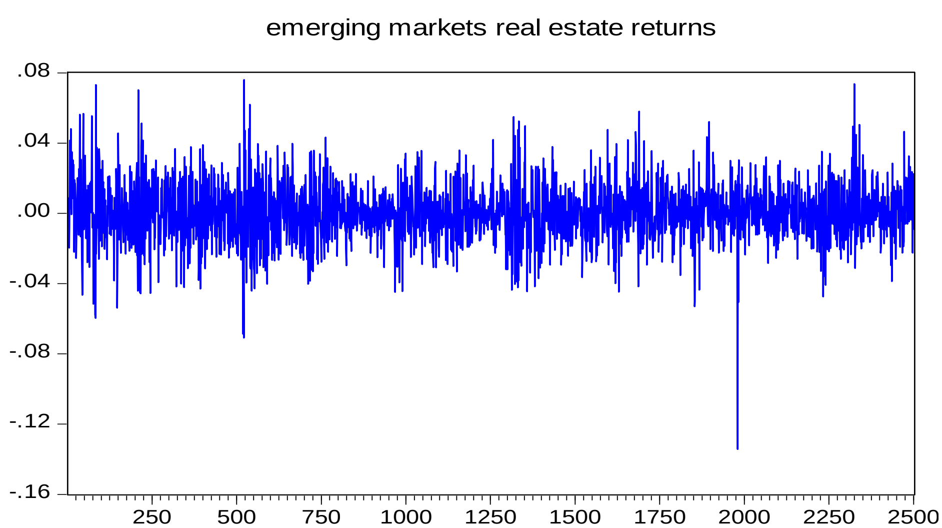

Figure 6.2: Volatility clustering of real estate returns

The existence of volatility clustering validates the appropriateness of the GARCH models.

6.1.2. EGARCH (1,1) model results for real estate

The EGARCH (1.1) model estimation results for real estate returns (dependent variable) in emerging markets are presented in Table 6.2 below (refer to Appendices 99-101):

Table 6.2: EGARCH estimation for real estate

Parameter (response variable)	**Normal**	**Student's T**	**GED**
C (constant)	-0.6646	-0.4323	-0.5080
α (garch effects)	0.18586	0.16392	0.169738
λ (leverage effects)	-0.029353	-0.04095	-0.035486
B (volatility persistence)	0.93674	0.9630	0.954228

Source: Author's extracts from Eviews

For all three error distributions, the results are significant at 1%. This implies the existence of 'GARCH' effects, meaning that current real estate return volatility levels are a function of past volatility. This makes forecasting and predicting volatility (and risk) a worthwhile task in an attempt to manage risk. The existence of leverage effects in the real estate segment in developing markets infers that investors in the sector overreact to negative shocks or news and underreact to positive shocks. Restated, negative shocks loom larger compared to positive jolts of the equivalent dimension. The presence of leverage effects means that the effect of a positive shock on real estate returns results in a fall in future volatility, while a negative shock leads to an upsurge of volatility.

High levels of volatility persistence in the real estate sector means emerging markets are inefficient as they require extended periods to impound news into current prices. In other words, once a shock (new information) is introduced into the market, it takes time to decay or die out. This erodes investor confidence and amplifies risk averseness of investors thereby promoting market illiquidity and reduced supply of capital in the real estate sector in emerging markets.

6.1.3. EGARCH (1,1) model results for emerging market stock returns

Volatility behavior of emerging market equity returns (dependent variable) following EGARCH specification is shown below (refer to Appendices 93-95).

Table 6.3: EGARCH estimation for emerging market general equity

Parameter (response variable)	**Normal**	**Student's T**	**GED**
C (constant)	-0.083638	-0.076263	-0.081391
α (garch effects)	0.102552	0.09210	0.097952
λ (leverage effects)	-0.088731	-0.090077	-0.088546
B (volatility persistence)	0.982855	0.984374	0.983491

Source: Author's extracts from Eviews

Results from the emerging market general stock returns are in harmony with the findings from infrastructure and real estate. This further supports the claim that listed infrastructure, real property and overall equity in emerging economies, are homogenous assets. The volatility features exhibited are of the same nature as those discussed above (using the EGARCH approach).

6.1.4. GJR-GARCH (1,1) model results for real estate

The results from the GJR-GARCH (1.1) model estimation using real estate returns (dependent variable) are presented in Table 6.4 below (refer to Appendices 117-119):

Table 6.4: GJR-GARCH estimation results for real estate

Parameter (response variable)	**Normal**	**Student's T**	**GED**
C (constant)	0.000	0.000	0.013387
arch term	0.073391	0.067236	-0.003785*
λ (leverage effects)	0.030354 *	0.048466	0.115739
Garch term	0.854865	0.870539	0.929472

Source: Author's extracts from Eviews

*indicates insignificant coefficients

The 'ARCH' effect is not significant, considering the GED meaning that the size of past errors is not significant in determining current volatility of real estate returns in emerging nations. Leverage effects are not significant for normal error distributions, implying that the impacts of both positive and negative shocks on future real estate return volatility are symmetrical (of equal size). Significant volatility persistence (computed by adding all the mean variance coefficients, save for the constant term), result in increased cost of capital and reduced private investment in the real sector in emerging nations.

6.1.5. GJR-GARCH (1,1) model results for general stock returns

Considering the general stock returns (dependent variable) in emerging markets, the resultant volatility features are presented in Table 6.5 below (refer to Appendices 120-122):

Table 6.5: GJR-GARCH estimation results for general equity

Parameter (response variable)	**Normal**	**Student's T**	**GED**
C (constant)	0.014115	0.013387	0.0140
arch term	0.000*	-0.003785*	-0.00167*
λ (leverage effects)	0.1175	0.115739	0.11609
garch term	0.924983	0.929472	0.92599

Source: Author's extracts from Eviews

*indicates insignificant parameters

The absence of ARCH effects coupled with significant leverage effects on the general emerging stock markets returns, means the impact of previous residuals on the current volatility comes from the leverage component. Existence of significant volatility persistence in the stock market returns in emerging markets reduces stock market participation, thereby promoting market illiquidity. Persisting volatility brings uncertainty for company prospects. This tends to nurture inefficient capital allocation as listed firms require significant reserves to reassure regulatory authorities of their soundness and financial stability.

6.1.6. Forecasting ability of volatility models

In evaluating the forecasting ability of the models used, the results obtained are presented hereunder. Table 6.6 below display the loss function measures for real estate using the EGARCH specification of the first order (refer to Appendices 126-128).

Table 6.6: EGARCH loss function for real estate

Loss function	**Normal**	**Student's T**	**GED**
RSME	0.168	0.0167	0.0168
MAE	0.126	0.0126	0.0126

Source: Author's extracts from Eviews

Though the measures are very low, EGARCH specification under the GED gives the best results in modeling and forecasting real estate volatility in developing economies.

Considering GJR-GARCH, the results from the loss function are presented in Table 6.7 (refer to Appendices 117-119).

Table 6.7: GJR-GARCH loss function for real estate

Loss function	**Normal**	**Student's T**	**GED**
RSME	0.0168	0.0168	0.017
MAE	0.0126	0.0126	0.0126

Source: Author's extracts from Eviews

As with EGARCH specification, GJR-GARCH under GED provides optimal modeling and forecasting real property return volatility in emerging markets. Comparing the two specifications or models, GJR-GARCH is superior to EGARCH in exposing volatility features of real estate returns in emerging economies.

Results for forecasting ability of volatility models under consideration regarding general emerging market stock variance is shown are Table 6.8.

Table 6.8: EGARCH loss function for emerging market stock returns

Loss function	**Normal**	**Student's T**	**GED**
RSME	0.965	0.9649	0.9649
MAE	0.7096	0.7089	0.7087

Source: Author's extracts from Eviews

In estimating and modeling volatility of emerging stock, EGARCH under normal distribution gives optimal results (refer to Appendices 123-125). Using the GJR-GARCH specification, the loss function results are presented in Table 6.9.

Table 6.9: GJR-GARCH loss function for emerging market stock returns

Loss function	**Normal**	**Student's T**	**GED**
RSME	0.965	0.965	0.965
MAE	0.710	0.709	0.709

Source: Author's extracts from Eviews

The results are also in favor of normal distribution (refer to Appendices 120-122). Thus, in order to fully capture volatility features of stock returns in emerging markets, assumption of normal distribution using GJR-GARCH model yields optimal results. GJR-GARCH is superior to EGARCH model when it comes to modeling and forecasting emerging market stock returns volatility.

CHAPTER 7

FINDINGS, CONCLUSIONS, IMPLICATIONS AND RECOMMENDATIONS

7.0. Introduction

In light of the five research papers presented in Chapters 3-5 (augmented in Chapter 6), this present chapter briefly focuses on the key results of the research, and draws conclusions based on these findings. It also offers plausible recommendations and implications to investors, infrastructure companies, lenders and policy makers. The first part provides the main outcomes, conclusions, implications and recommendations of the study, objective by objective. The second section gives the overall findings and conclusions of the whole thesis as a single research thread.

The research papers presented in the preceding chapters collectively evaluated the claimed intrinsic investment features in emerging markets using appropriate methods relative to past studies. Thus the research papers form a single continuous thread from the third to the sixth chapter. The investment features assessed include the inflation hedging and return enhancing ability of infrastructure relative to other asset classes. With focus on emerging markets after the world-wide financial crisis of 2007/8, the papers covered the era after major shifts in investor sentiments regarding their traditional portfolio allocations.

7.1. Key findings, implications, and recommendations of the study

This section presents the findings implications, conclusions and recommendations per objective in brief as the details have already been covered in Chapters 3-5. Due to the fact that almost the same data sets were used for all the objectives, the findings on distributional features, risk-return profiles and correlations, are the same. Thus, such features are highlighted only under objective one.

7.1.1. Objective 1- Performance enhancing ability of infrastructure investments

Findings from objective 1

Key findings from objective 1, when looking at the performance enhancing and risk reduction ability of the infrastructure sector in emerging markets, were as follows:

Unlisted or private infrastructure enhances portfolio performance

The study used the four assets under study (unlisted infrastructure, listed infrastructure, real estate and emerging market average equity returns) to construct an optimal portfolio, using the mean-variance portfolio optimization approach. Adding one asset at a time, portfolios containing unlisted infrastructure had the highest Sharpe ratio (risk-adjusted return measure) relative to other portfolios without unlisted infrastructure. Expectedly, the weights of most optimal portfolios were skewed towards the unlisted infrastructure asset. This indicates that unlisted infrastructure is a portfolio 'performance enhancer'.

Listed infrastructure in emerging markets does not add any value to a traditional portfolio made up of listed real estate and general equity. As listed infrastructure and other listed assets are positively correlated, they can be treated as substitutes. Unless institutional investors consider other factors besides risk and return when making an asset allocation decision, it is of no value to include listed infrastructure in a traditional portfolio.

Unlisted infrastructure earned higher than other assets in emerging markets

Using yearly and quarterly returns, unlisted infrastructure earned returns above real estate, listed infrastructure and emerging markets for all stock returns. Unlisted infrastructure earned above the risk free rate in emerging markets during the era under study, whilst all remaining assets failed to outperform the risk free asset. Before adjusting for risk, unlisted infrastructure earned more (on average) than other asset classes on a yearly and quarterly basis. Considering risk attuned return measures namely; the Sharpe ratio and Sortino ratio, unlisted infrastructure generated the highest positive ratios on both a yearly and quarterly basis. On the contrary, listed infrastructure generated negative Sharpe and Sortino ratios on a yearly and quarterly basis. Thus, listed infrastructure failed to generate superior returns as per its widely accepted investment narrative or attribute.

Unlisted and listed infrastructure investments exhibited different stochastic and distributional features

An interesting phenomenon was found when considering the statistical and correlational link between exchange traded and private infrastructure investments. The results showed a negative correlation coefficient between the two variables, suggesting that they can play a complementary role in a portfolio. The differences were notable, considering average yearly and quarterly returns (and risk-adjusted returns), as they were skewed towards unlisted infrastructure. This boggles the mind of any rational investor as we expect the distributional features to be the same. This is because logic dictates that listed and private infrastructure are actually equivalent save that one is listed on stock markets and the other is not. The findings for this objective are in contrast to the claim by De Bever, Van Nieuwerburgh, Stanton & Berkeley, (2015), who professed that as the investment horizon increases, listed and unlisted infrastructure asset investment features converge, making the two close substitutes, thereby providing room for investors to swap listed for unlisted infrastructure investment. This distributional and correlational heterogeneity could be attributed to differences in liquidity, price transparency issues and risk-return profiles. On the same note, market inefficiency most pronounced in markets for listed assets might be another plausible explanation. Such markets are prone to irrational behavior arising from investors' psychological biases and errors. Since the prices of listed assets are determined in the open market, they are likely to be affected by these non-fundamental attributes on an on-going basis (Bruce, 2017).

Conclusions for objective 1

Based on the above outlined findings, the following conclusions can be drawn;

Institutional investors can enhance portfolio performance using unlisted infrastructure

Including unlisted infrastructure as part of a risky portfolio enhances the risk-adjusted returns earned by institutional investors exposed to emerging markets. This emanates from the fact that unlisted infrastructure earned far above other assets under study (in absolute and risk-adjusted terms). In other words, 'performance seeking' goals pursued by institutional investors can be achieved using unlisted infrastructure.

Unlisted and listed infrastructure investments are complementary

Given the differences between listed and private infrastructure (taking into account risk-return profiles, correlation with remaining assets and between themselves), these two assets can be treated as complementary and not as substitutes. This means they can be part of the same portfolio and reduce portfolio risk. Restated, it makes economic sense for institutional investors with interests in emerging markets to hold onto listed and unlisted infrastructure simultaneously as listed infrastructure assets are treated and priced differently from privately held infrastructure assets.

Unlisted infrastructure generates superior risk-adjusted returns

Institutional investors can generate superior risk adjusted returns by owning unlisted infrastructure investments. This claim does not hold for listed infrastructure investments in emerging markets.

Implications for investors

In view of the above findings and conclusions, the following implications arise:

The first implication for institutional investors is that for them to draw some value (better risk adjusted returns) from the infrastructure sector, they must use the unlisted investment route.

The findings from the first objective imply that investors with interests in emerging markets should not expect better rewards for investing in emerging market listed infrastructure if they are already invested in general stock from developing economies. This is based on the fact that the risk-return profile of general stock in developing economies is actually favorable compared to listed infrastructure.

Another implication is that institutional investors must treat listed and unlisted infrastructure investments as complements (not as substitutes), as their stochastic behavior and risk-return profiles are different. The skewed differences between listed and unlisted infrastructure implies that other things being equal, the value of an unlisted infrastructure firm is higher than its listed counterpart.

Recommendations to investors and researchers

Based on the results and deductions outlined above, the subsequent recommendations are submitted;

Infrastructure firms are encouraged to increase information availability to the public and analysts so that their assets are rationally priced. It is not expected that a firm's value will be volatile and low, simply because it is listed whilst its counterpart's value is stable and high simply because it is privately held. Such inconsistencies might affect the credit rating of the firm, thereby negatively affecting the firm's value.

Institutional investors interested in emerging economies are recommended to consider the heterogeneous nature of the infrastructure sector. When investing in the infrastructure sector, institutional investors are encouraged to take note of the differences between infrastructure investment categories. If notable differences can be noted between listed and unlisted infrastructure, it is expected that investment features are likely to be different between for example, economic and social infrastructure (Moss, 2014; Bever *et al.,* 2015).

Institutional investors with interests in the emerging market infrastructure sector are recommended to continue monitoring the developments in the infrastructure market due to the fact that as sectors grow and mature, increased deregulation, informational efficiency and privatization become the order of the day, rendering the ability of unlisted infrastructure to deliver super returns, extinct (Bird et al., 2014).

Further studies could focus on infrastructure sector sub-categories to cater for the heterogeneous nature of this sector in emerging markets (Inderst, 2016). The same can be said of the need to unbundle the emerging market category, as the market is also heterogeneous and generalizations might not be appropriate (Moore, 2018). On the same note, other risk-attuned return methods such as the Omega quotient and Jensen's Alpha could be considered in further research. As more data becomes available, longer periods might be used by researchers to further the argument.

7.1.2. Objective 2 - portfolio risk diversification ability of infrastructure

Findings on objective 2

The following key findings were drawn on objective 2:

Unlisted infrastructure exhibited investment attribute of reducing portfolio risk

The overall power of reducing portfolio risk by investing in private or unlisted infrastructure is evident in portfolios containing unlisted or private infrastructure. Such portfolios exhibited the highest risk-adjusted return scores relative to other portfolios. Optimal portfolios containing unlisted infrastructure exhibited the lowest standard deviation relative to other portfolios, thereby indicating the ability of unlisted infrastructure to dampen portfolio risk. This is based on the fact that even at individual asset level, unlisted infrastructure exhibited the lowest standard deviation value (indicating lowest volatility), relative to other assets under consideration.

Private infrastructure is inversely correlated with all asset groups in emerging economies

Private infrastructure exhibited negative correlation with all the assets under consideration, illustrating its ability to reduce risk in a risky portfolio. This concurs with Bahceci and Leh's (2017) assertion, pointing to the fact that portfolio risk reduction can be achieved by including private infrastructure in a varied portfolio comprised of listed equities, listed real estate and listed infrastructure in emerging markets.

Listed infrastructure failed to effectively reduce portfolio risk

As listed infrastructure exhibited positive correlation with other risky assets, its ability to dampen portfolio risk is lower relative to unlisted infrastructure. On the same note, the volatility of listed infrastructure (measured by standard deviation) is comparatively high, thereby penalizing its ability to reduce portfolio risk. Similar findings were evident in real estate and general emerging market stock returns.

Conclusions on objective 2

Centered on the discoveries made, the subsequent suppositions were made for objective 2:

Institutional investors can dampen portfolio risk using unlisted infrastructure.

Adding unlisted infrastructure to a risky portfolio effectively reduces portfolio risk in emerging markets for institutional investors.

Listed infrastructure is not a portfolio risk diversifier.

Investors in emerging markets are not in a position to diversify portfolio risk using listed infrastructure, as evidenced by negative risk-adjusted returns.

Implications

Investors can drive some risk diversification benefits by allocating a substantial amount of their resources to unlisted infrastructure. It must be noted that such a benefit should be taken cognizant of the demerits associated with unlisted infrastructure investments, such as lack of liquidity, lack of pellucidity and possibly huge trading fees.

Unless investors are pursuing other goals besides risk and return, there is no economic or rational reason to include exchange traded infrastructure and real property in their portfolios if they are already invested in emerging market general stocks.

Recommendation

Against the mentioned findings and implications, investors interested in the emerging infrastructure sector are recommended to include unlisted infrastructure in their risk portfolios to reduce portfolio risk. On the same note, the investors must be on the look-out for the liquidity risk and transaction costs incurred in the unlisted infrastructure investment market.

7.1.3. Objective 3- Inflation hedging ability of infrastructure

As highlighted in Chapter 4, evaluation of the inflation ability of the infrastructure sector (relative to other assets), was achieved using three different approaches. As such, a snapshot of all the three approaches is given hereunder.

Major findings

Using the ARDL approach, unlisted infrastructure, real estate and emerging market general stock, exhibited an insignificant relationship with inflation on a short and long term basis. Restated, all the assets failed to exhibit inflation hedging capabilities in emerging markets.

Inflation lagged two quarters was noted to be momentous and positively linked to listed infrastructure in emerging markets on a short term basis. The coefficient is significantly above unit, indicating that listed infrastructure investments are perfect hedges of general price increases in support of the Fama-Schwert (1977) hypothesis.

Applying the PARDL model, all assets under consideration (listed infrastructure, real estate and individual nation stock market average returns), were not significantly related to inflation on a long and short term basis.

Utilizing the NARDL approach**,** the effect of long and short run positive and negative inflation shocks were insignificant in all assets under consideration. In other words, infrastructure investments (listed and unlisted), real estate and emerging market general equity in emerging economies, were found to be poor asymmetric inflation hedgers.

Conclusions

Listed infrastructure investments hedge lagged inflation (previous period inflation rates) **-** not current inflation rates- in the short run.

Unlisted infrastructure, real estate and emerging market general equity are not good inflation hedges in emerging markets.

Implications

Inability of assets to hedge inflation implies the existence of significant beta risk in emerging stock markets. This means that when the economy is heading north or south, all assets under consideration follow suit (no sacred cows).

Results imply poor pricing powers among infrastructure firms. Such is expected, given that infrastructure sector deregulation is still gathering momentum in emerging markets and prices of infrastructure services are regulated by government agencies who take time to approve price changes. To add to this, if firms can increase prices in line with inflation, reduced aggregate demand and sales volume off-set this advantage, leading to lower cash-flows to stockholders. Restated, the negative effects of inflation on consumers, aggregate demand, present value of dividends and sales volume, far outweigh the positive impact of general price increases on inflation-linked revenues, and salaries.

Inflation illusion might be significant among financial market participants in emerging markets, with investors discounting the positive impact of inflation on nominal earnings, simultaneously compounding the negative effect of inflation on current values.

Recommendations to investors, policy makers and researchers

Financial market participants (especially long term investors), should consider other assets like commodities, currencies and precious metals as alternatives in their quest to hedge inflation in emerging markets.

Policy makers in the infrastructure sector are recommended to come up with concessions and agreements which link returns and earnings from the infrastructure sector to inflation. Such a strategy will promote the availability of private capital for infrastructure investments; these are long term in nature.

Further research could decompose the actual rate of general price increases into anticipated and unanticipated inflation and assess the infrastructure sector's ability to hedge the same. Research could also be carried out, evaluating the inflation hedging capacity of this sector under different inflation regimes (walking, galloping and hyper-inflation), as this study was carried out in a low inflation environment.

7.1.4 Objective 4- volatility behavior of infrastructure investments

Findings

Results from both GJR-GARCH and EGARCH models under all distributions exhibited the following;

GARCH and ARCH effects were generally significant:
Considering all error distributions and both symmetric volatility models, the GARCH and ARCH effects were positive and significant in the returns of the emerging markets' infrastructure and real estate sector, indicating that past volatility and residuals or errors are significant in predicting current volatility. Emerging markets' infrastructure sector returns have a significant response to the absolute size of the shock. On the same note, volatility clustering was found to be significant, indicating that a period of high (low) volatility or swings is followed by a period of high (low) volatility in the infrastructure and real property sector in emerging markets.

Using the GJR-GARCH approach, ARCH effects were absent in emerging market general stock returns. This indicates that past errors are not significant in predicting current volatility levels of general stock returns in emerging markets.

Volatility persistence was exhibited in emerging markets' infrastructure sector returns.
The level of volatility persistence was very high and significant, indicating that once a shock is introduced to the infrastructure sector in emerging markets, it takes time to die out as it has a long memory. This persistence is normally attributed to market inefficiency (whereby information is slowly assimilated and captured in stock prices), and the momentum effect - which is a behavioral bias. Real estate and general stock market returns in emerging markets exhibited similar volatility persistence.

Leverage effects existed in the infrastructure sector of emerging nations:
The leverage effect coefficient is less than zero and significant, indicating the existence of an asymmetric response to bad (negative) and good (positive) news by investors in the emerging markets' infrastructure sector. The impact of negative news on future conditional volatility is larger than the effect of positive news. In other words, volatility responds more to negative shocks than positive shocks

of the equivalent size. Similar findings were noted in real estate and general equity market yields in emerging markets.

From the forecasts made, the GJR-GARCH model performed better than the EGARCH model in all error distributional assumptions.

Conclusions

Volatility clustering, volatility persistence and leverage effects characterize volatility behavior of exchange traded infrastructure securities, real property and general stock returns in developing economies.

Listed infrastructure exposes investors to similar volatility aspects as real estate and general stock market returns in developing economies.

GJR-GARCH model of order one is superior in modeling and forecasting exchange traded infrastructure, real estate and general stock returns in emerging markets.

Implications

The existence of significant volatility persistence in emerging markets' infrastructure stock returns implies that shocks in the sector take time to die out, causing the dampening of investor confidence, an increase in the cost of capital and a fall in private investment.

The fact that the leverage effects and GARCH effects are both significant implies that as the asymmetric impact of innovations is accounted for, the absolute size of the innovation is equally important. Consequently, previous conditional variance and past residuals are significant in determining today's conditional variance, thereby making forecasting a worthwhile task. This might be of assistance to investors, firms and money managers interested in making hedging and speculating decisions on volatility in the infrastructure sector and real property and stock markets in emerging economies.

The results imply that as infrastructure firms and real estate firms operating in emerging markets are negatively affected by the existence of volatility persistence, they require significant reserves of cash and cash-equivalent assets in order to assure creditors and other stakeholders of their stability and soundness. Such an activity will lead to poor or inefficient allocation of resources as significant amounts of capital are reserved to solely assure authorities that the firm is sound and stable. On the same note, volatility persistency results in the increased cost of providing liquidity, leading to a fall in supply of long term capital.

Stock market development is threatened when significant volatility persistence is exhibited, although abnormal returns can be earned. Consequently, the value attached to firms in the infrastructure and real estate sectors in emerging markets is comparatively lower than those in stable and efficient financial environments.

The volatility features exhibited imply that investors interested in the infrastructure sector in emerging markets might underestimate value-at-risk if they ignore leverage effects, and excess kurtosis in their estimation of value-at-risk.

Recommendations to investors, policy makers and researchers

Institutional investors are recommended to go beyond mean-variance portfolio optimization and consider leverage effects, excess kurtosis and skewness when making investment decisions and when revising their portfolios in developing economies.

Corporates in the infrastructure sector in developing economies should be prepared to absorb an additional risk premium as lenders are exposed to significant volatility persistence. This is due to the fact that volatility persistence has a tendency to surge risk averseness of investors at large, such that significant premiums are required to induce them to invest in the sectors under study.

Investors in the infrastructure and real estate sectors in emerging markets should also formulate hedging strategies as they are exposed to significant risk and uncertainty. On the same note, investors should also come up with other sources of liquidity as volatility persistence will increase the cost of providing liquidity in emerging markets.

It is recommended that financial regulators in emerging markets should formulate policies which dampen market volatility. For example, policy makers might reduce negative news emanating from policy inconsistencies, and macro-economic instability at large. Such policies will promote stock market developments making long term funds easily accessible and affordable. Restated, regulatory authorities are encouraged to design policies which promote well-functioning, and stable financial markets. Otherwise, investors will require a risk premium, increasing the cost of capital and hampering the availability of long term capital, thereby dampening the prospects of economic growth.

As the above outline is paper or objective specific, the following section spells out the overall findings, conclusions and recommendations for the whole study.

7.2. General findings

Unlisted infrastructure exhibited a favorable investment feature which can be attractive to long term investors in their pursuit of performance and portfolio risk reduction objectives. However, the asset failed to display any performance enhancing ability or portfolio risk diversification capabilities in emerging markets.

Overall, unlisted and listed infrastructure assets are complements as they have different risk-return profiles. As such, they can be part of the same portfolio and generate positive benefits like enhanced portfolio performance and liquidity for investors.

Listed infrastructure (transportation, utilities, energy, social and telecommunication sectors) displayed some degree of inflation hedging in the short run. Unlisted infrastructure, real estate as well as general equity market returns in emerging markets, exhibited poor inflation capabilities in both the short and long run.

All assets under study displayed volatility clustering, volatility persistence and leverage effects. Thus, no significant difference was noted among the assets under study as far as volatility issues are concerned.

7.3. General conclusions

These are specified as follows:

Unlisted infrastructure enhances portfolio performance.

Unlisted infrastructure dampens portfolio risk.

Infrastructure, like all other assets under consideration, is not a good inflation hedge. It is good as it provides owners with some control of the company resources but not as a tool to hedge inflation risk.

Volatility clustering, volatility persistence and leverage effects characterize the infrastructure sector, real estate and general stock market returns in emerging markets.

In a nutshell, institutional investors can generate enhanced portfolio returns and portfolio risk diversification by investing in unlisted infrastructure in emerging markets.

7.4. Overall implications

Investors can use unlisted infrastructure investments in emerging markets to enhance their portfolio performance and reduce portfolio risk.

Listed and private infrastructure securities can be in the same portfolio and generate positive returns for portfolio owners.

Investors might need to consider other assets (not included in this study) and commodities in their quest to hedge inflation risk.

Investors in infrastructure, real property sectors and the general equity market in emerging markets must be prepared to assume high levels of uncertainty and liquidity challenges.

Firms operating in the infrastructure and real property sectors must be prepared to reserve significant capital amounts to prove their soundness and stability. On the same note, such firms are likely to be charged a higher cost of capital relative to their counterparts in less volatile markets.

7.5. Overall recommendations

Investors are recommended to allocate a significant part of their capital to unlisted infrastructure so that they can enhance their portfolio performance and reduce portfolio diversifiable risk.

In order to hedge inflation risk, investors are recommended to look beyond infrastructure, real property and the general equity market in emerging markets.

Policy makers in emerging companies are recommended to design contracts and concessions which link returns from long term infrastructure returns to inflation rate. On the same note, regulators in emerging financial markets are recommended to come up with macro-economic stabilization policies to restore investor confidence, thereby attracting long term capital.

Investors are encouraged to consider leverage effects when computing their value-at-risk figures and when making investing decisions.

Researchers are encouraged to unbundle the infrastructure sector, and emerging markets ‘groups’ when making future studies. On the same note, as data become available and the economic environment changes, inflation hedging capabilities of the assets covered in this study can be evaluated on a longer term basis in different inflation environments.

7.6. Overall contributions to body of knowledge

From the emerging market perspective, the current study made the following contributions to the existing body of knowledge (cognizant of the fact that past studies were largely industrial bulletins in developed nations):

This present research furthers the discussion on the role of infrastructure investments by considering the issue in emerging markets and applying robust approaches and econometric tests.

The knowledge gap in the performance and features of infrastructure investments in emerging markets is greatly reduced by the institution of this study.

The study confirms the performance enhancing and risk diversification ability of unlisted infrastructure (relative to other assets) in emerging markets.

Applying portfolio optimization and risk-adjusted return measures, this thesis denounced the claim that listed infrastructure can enhance portfolio performance and reduce portfolio risk in emerging markets

This present study supported an interesting claim that listed and private infrastructure securities are heterogeneous, using a plethora of tests and econometric approaches.

The study refuted the common hypothesis that infrastructure investment hedge inflation risk in emerging markets. This was done using linear and non-linear approaches.

Applying symmetric volatility models using the three sets of error distributions, the study refutes the hypothesis that listed infrastructure exhibits different volatility features from other listed assets.

7.7. Summary of the study

In their quest to enhance portfolio returns and meet their long term objectives, investors are in search for alternative assets which can offer them predictable, less volatile and inflation linked returns. The search for better yields accentuated throughout the crisis and after the world-wide financial crisis of 2007/8, as the assets which used to be the favorites, failed to provide steady returns.

Given the appetizing infrastructure investment features (well documented in industrial bulletins), and the needs of institutional investors, the link between the two seem to be natural and a win-win scenario (at least narratively). What is lacking is the academic evidence to substantiate the claim that infrastructure is now the new investment niche which long term investors can embrace in order to generate superior steady inflation linked returns.

As past scant academic literature is largely from developed nations applying basic statistical methods, this study transposed the evaluation to emerging markets, using better econometric approaches and relatively longer data sets. The available academic studies lack consensus as to the role of infrastructure investments in a risky portfolio and their ability to hedge inflation. The same applies to the risk profile of infrastructure investments.

The infrastructure market is still young and evolving, such that it is expected to find different features and trends in emerging markets than those obtaining in developed nations. As such, this study exhumed such investment features of infrastructure investments relative to comparable assets. This thesis evaluated the investment attributes of infrastructure in emerging markets over the post-crisis 10 year period. Applying portfolio optimization procedures and risk-adjusted return measures, it was noted that unlisted infrastructure enhances portfolio performance and dampens portfolio risk. On the same note it was observed that exchange traded and unlisted infrastructure securities are complements. Using linear and non-linear approaches, it was established that infrastructure like real estate and general stock market returns, cannot effectively hedge inflation risk. Applying asymmetry volatility methods, the study established that all the assets under study share similar volatility or risk features in emerging markets.

Against these findings and conclusions, the study recommended that investors be wary of the volatility features when making investment decisions and managing risk. Policy makers in emerging markets were encouraged to come up with economic stabilization policies to improve investor confidence, thereby fostering stock market and economic development. Researchers were encouraged to decompose inflation (into expected and unexpected) and infrastructure (into sub-sectors) as data becomes available, to further the argument under study.

ETHICAL CLEARANCE LETTER

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

Mr Rabson Magweva (216073100)
School Of Acc Economics&Fin
Westville

Dear Mr Rabson Magweva,

Protocol reference number: 00002209
Project title: significance of infrastructure investments to institutional investors in emerging markets

Exemption from Ethics Review

In response to your application received on 18 June 2019, your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

UKZN Research Ethics Office
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Website: http://research.ukzn.ac.za/Research-Ethics/

Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

INSPIRING GREATNESS

TURN-IT-IN REPORT

PhD draft

ORIGINALITY REPORT

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SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

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7	Submitted to University of Durham Student Paper	<1%
8	Submitted to University of Reading Student Paper	<1%
9	Submitted to University of Glasgow	

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APPENDICES

Appendix 1: Unlisted infrastructure unit root test using ADF

Null Hypothesis: D(UNLISTEDINFRA) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.621101	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNLISTEDINFRA,2)
Method: Least Squares
Date: 01/23/20 Time: 07:00
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(UNLISTEDINFRA(-1))	-0.856612	0.129376	-6.621101	0.0000
C	0.212592	0.225071	0.944556	0.3512

R-squared	0.549092	Mean dependent var	0.149474
Adjusted R-squared	0.536567	S.D. dependent var	2.036238
S.E. of regression	1.386187	Akaike info criterion	3.542187
Sum squared resid	69.17454	Schwarz criterion	3.628376
Log likelihood	-65.30155	Hannan-Quinn criter.	3.572852
F-statistic	43.83897	Durbin-Watson stat	1.878577
Prob(F-statistic)	0.000000		

Appendix 2: Unlisted infrastructure unit root test using Phillips-Perron

Null Hypothesis: D(UNLISTEDINFRA) has a unit root
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.411270	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	1.820383
HAC corrected variance (Bartlett kernel)	2.505371

Phillips-Perron Test Equation
Dependent Variable: D(UNLISTEDINFRA,2)
Method: Least Squares
Date: 01/23/20 Time: 07:01
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(UNLISTEDINFRA(-1))	-0.856612	0.129376	-6.621101	0.0000
C	0.212592	0.225071	0.944556	0.3512

R-squared	0.549092	Mean dependent var	0.149474
Adjusted R-squared	0.536567	S.D. dependent var	2.036238
S.E. of regression	1.386187	Akaike info criterion	3.542187
Sum squared resid	69.17454	Schwarz criterion	3.628376
Log likelihood	-65.30155	Hannan-Quinn criter.	3.572852
F-statistic	43.83897	Durbin-Watson stat	1.878577
Prob(F-statistic)	0.000000		

Appendix 3: Unlisted infrastructure unit root test using KPSS

Null Hypothesis: UNLISTEDINFRA is stationary
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.340164
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	12.30070
HAC corrected variance (Bartlett kernel)	44.13016

KPSS Test Equation
Dependent Variable: UNLISTEDINFRA
Method: Least Squares
Date: 01/23/20 Time: 07:02
Sample: 2009Q1 2018Q4
Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.82500	0.561607	22.83625	0.0000

R-squared	0.000000	Mean dependent var	12.82500
Adjusted R-squared	0.000000	S.D. dependent var	3.551915
S.E. of regression	3.551915	Akaike info criterion	5.397533
Sum squared resid	492.0278	Schwarz criterion	5.439755
Log likelihood	-106.9507	Hannan-Quinn criter.	5.412799
Durbin-Watson stat	0.235103		

Appendix 4: Unlisted infrastructure unit root test using Ng-Perron

Null Hypothesis: D(UNLISTEDINFRA) has a unit root
Exogenous: Constant
Lag length: 0 (Spectral GLS-detrended AR based on SIC, maxlag=9)
Sample: 2009Q1 2018Q4
Included observations: 40

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-3.62093	-1.34503	0.37146	6.76627
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

HAC corrected variance (Spectral GLS-detrended AR)	2.807514

Appendix 5: Listed infrastructure unit root test using ADF

Null Hypothesis: D(LISTEDINFRA) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.743849	0.0000
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LISTEDINFRA,2)
Method: Least Squares
Date: 01/23/20 Time: 07:15
Sample (adjusted): 2009Q4 2018Q4
Included observations: 37 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LISTEDINFRA(-1))	-1.683115	0.249578	-6.743849	0.0000
D(LISTEDINFRA(-1),2)	0.373999	0.158252	2.363313	0.0240
C	-0.983469	2.214297	-0.444145	0.6598

R-squared	0.662564	Mean dependent var	0.691341
Adjusted R-squared	0.642715	S.D. dependent var	22.42932
S.E. of regression	13.40676	Akaike info criterion	8.107000
Sum squared resid	6111.200	Schwarz criterion	8.237615
Log likelihood	-146.9795	Hannan-Quinn criter.	8.153048
F-statistic	33.37989	Durbin-Watson stat	1.864238
Prob(F-statistic)	0.000000		

Appendix 6: Listed infrastructure unit root test using Phillips-Perron

Null Hypothesis: LISTEDINFRA has a unit root
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.694869	0.0080
Test critical values:	1% level	-3.610453	
	5% level	-2.938987	
	10% level	-2.607932	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	148.4132
HAC corrected variance (Bartlett kernel)	155.4213

Phillips-Perron Test Equation
Dependent Variable: D(LISTEDINFRA)
Method: Least Squares
Date: 01/23/20 Time: 07:16
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LISTEDINFRA(-1)	-0.541482	0.148434	-3.647973	0.0008
C	-0.202546	2.002959	-0.101123	0.9200

R-squared	0.264526	Mean dependent var	-0.297403
Adjusted R-squared	0.244649	S.D. dependent var	14.39107
S.E. of regression	12.50742	Akaike info criterion	7.940442
Sum squared resid	5788.115	Schwarz criterion	8.025752
Log likelihood	-152.8386	Hannan-Quinn criter.	7.971050
F-statistic	13.30771	Durbin-Watson stat	1.877899
Prob(F-statistic)	0.000810		

Appendix 7: Listed infrastructure unit root test using KPSS

Null Hypothesis: D(LISTEDINFRA) is stationary
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.041486
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	201.7927
HAC corrected variance (Bartlett kernel)	155.3177

KPSS Test Equation
Dependent Variable: D(LISTEDINFRA)
Method: Least Squares
Date: 01/23/20 Time: 07:18
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.297403	2.304416	-0.129058	0.8980

R-squared	0.000000	Mean dependent var	-0.297403
Adjusted R-squared	0.000000	S.D. dependent var	14.39107
S.E. of regression	14.39107	Akaike info criterion	8.196400
Sum squared resid	7869.914	Schwarz criterion	8.239055
Log likelihood	-158.8298	Hannan-Quinn criter.	8.211704
Durbin-Watson stat	2.397334		

Appendix 8: Listed infrastructure unit root test using Ng-Perron

Null Hypothesis: D(LISTEDINFRA) has a unit root
Exogenous: Constant
Lag length: 2 (Spectral GLS-detrended AR based on SIC, maxlag=9)
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-3.79508	-1.35620	0.35736	6.46693
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

HAC corrected variance (Spectral GLS-detrended AR)	53.00061

Appendix 9: Emerging markets general stock unit root test using ADF

Null Hypothesis: D(EMALLSTOCK) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.910335	0.0000
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EMALLSTOCK,2)
Method: Least Squares
Date: 01/23/20 Time: 07:28
Sample (adjusted): 2009Q4 2018Q4
Included observations: 37 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EMALLSTOCK(-1))	-1.977400	0.249977	-7.910335	0.0000
D(EMALLSTOCK(-1),2)	0.409813	0.143439	2.857061	0.0072
C	-0.452440	0.576262	-0.785128	0.4378

R-squared	0.756520	Mean dependent var	0.058649
Adjusted R-squared	0.742197	S.D. dependent var	6.873762
S.E. of regression	3.490102	Akaike info criterion	5.415344
Sum squared resid	414.1476	Schwarz criterion	5.545959
Log likelihood	-97.18386	Hannan-Quinn criter.	5.461392
F-statistic	52.82087	Durbin-Watson stat	2.100999
Prob(F-statistic)	0.000000		

Appendix 10: Emerging markets general stock unit root test using Philips-Perron

Null Hypothesis: D(EMALLSTOCK) has a unit root
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-15.60538	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	13.51545
HAC corrected variance (Bartlett kernel)	3.451193

Phillips-Perron Test Equation
Dependent Variable: D(EMALLSTOCK,2)
Method: Least Squares
Date: 01/23/20 Time: 07:29
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EMALLSTOCK(-1))	-1.385049	0.140947	-9.826737	0.0000
C	-0.355500	0.612741	-0.580180	0.5654

R-squared	0.728435	Mean dependent var	-0.309211
Adjusted R-squared	0.720891	S.D. dependent var	7.149391
S.E. of regression	3.777077	Akaike info criterion	5.546974
Sum squared resid	513.5872	Schwarz criterion	5.633163
Log likelihood	-103.3925	Hannan-Quinn criter.	5.577639
F-statistic	96.56475	Durbin-Watson stat	2.365993
Prob(F-statistic)	0.000000		

Appendix 11: Emerging markets general stock unit root test using KPSS

Null Hypothesis: EMALLSTOCK is stationary
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.271819
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	10.51536
HAC corrected variance (Bartlett kernel)	11.88384

KPSS Test Equation
Dependent Variable: EMALLSTOCK
Method: Least Squares
Date: 01/23/20 Time: 07:29
Sample: 2009Q1 2018Q4
Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.614000	0.519254	1.182466	0.2442

R-squared	0.000000	Mean dependent var	0.614000
Adjusted R-squared	0.000000	S.D. dependent var	3.284050
S.E. of regression	3.284050	Akaike info criterion	5.240714
Sum squared resid	420.6144	Schwarz criterion	5.282936
Log likelihood	-103.8143	Hannan-Quinn criter.	5.255980
Durbin-Watson stat	1.715917		

Appendix 12: Emerging markets general stock unit root test using Ng-Perron

Null Hypothesis:D(EMALLSTOCK) has a unit root
Exogenous: Constant
Lag length: 0 (Spectral GLS-detrended AR based on SIC, maxlag=9)
Sample: 2009Q1 2018Q4
Included observations: 40

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-19.1262	-3.05969	0.15997	1.39772
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

HAC corrected variance (Spectral GLS-detrended AR)	10.62675

Appendix 13: Real estate unit root test using ADF

Null Hypothesis: EMREAL has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.808173	0.0000
Test critical values:	1% level	-3.610453	
	5% level	-2.938987	
	10% level	-2.607932	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EMREAL)
Method: Least Squares
Date: 01/23/20 Time: 07:34
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMREAL(-1)	-0.950426	0.163636	-5.808173	0.0000
C	0.331410	0.653089	0.507450	0.6149

R-squared	0.476920	Mean dependent var	-0.046603
Adjusted R-squared	0.462783	S.D. dependent var	5.536846
S.E. of regression	4.058237	Akaike info criterion	5.689295
Sum squared resid	609.3638	Schwarz criterion	5.774606
Log likelihood	-108.9413	Hannan-Quinn criter.	5.719904
F-statistic	33.73488	Durbin-Watson stat	1.717374
Prob(F-statistic)	0.000001		

Appendix 14: Real estate unit root test using PP

Null Hypothesis: D(EMREAL) has a unit root
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-13.32330	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	19.34735
HAC corrected variance (Bartlett kernel)	10.71975

Phillips-Perron Test Equation
Dependent Variable: D(EMREAL,2)
Method: Least Squares
Date: 01/23/20 Time: 07:35
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EMREAL(-1))	-1.464885	0.133001	-11.01412	0.0000
C	-0.456049	0.733299	-0.621914	0.5379

R-squared	0.771154	Mean dependent var	-0.264774
Adjusted R-squared	0.764797	S.D. dependent var	9.318151
S.E. of regression	4.519093	Akaike info criterion	5.905696
Sum squared resid	735.1993	Schwarz criterion	5.991884
Log likelihood	-110.2082	Hannan-Quinn criter.	5.936361
F-statistic	121.3108	Durbin-Watson stat	1.873850
Prob(F-statistic)	0.000000		

Appendix 15: Real estate unit root test using KPSS

Null Hypothesis: D(EMREAL) is stationary
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.043087
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	29.87060
HAC corrected variance (Bartlett kernel)	9.932473

KPSS Test Equation
Dependent Variable: D(EMREAL)
Method: Least Squares
Date: 01/23/20 Time: 07:36
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.046603	0.886605	-0.052563	0.9584

R-squared	0.000000	Mean dependent var	-0.046603
Adjusted R-squared	0.000000	S.D. dependent var	5.536846
S.E. of regression	5.536846	Akaike info criterion	6.286034
Sum squared resid	1164.953	Schwarz criterion	6.328689
Log likelihood	-121.5777	Hannan-Quinn criter.	6.301338
Durbin-Watson stat	2.760023		

Appendix 16: Real estate unit root test using Ng-Perron

Null Hypothesis: EMREAL has a unit root
Exogenous: Constant
Lag length: 0 (Spectral GLS-detrended AR based on SIC, maxlag=9)
Sample: 2009Q1 2018Q4
Included observations: 40

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-19.3032	-3.10592	0.16090	1.27202
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

HAC corrected variance (Spectral GLS-detrended AR)	16.22691

Appendix 17: Inflation rate unit root test using ADF

Null Hypothesis: INFLATION_ has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.098926	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INFLATION_)
Method: Least Squares
Date: 01/23/20 Time: 06:46
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INFLATION_(-1)	-1.270450	0.208307	-6.098926	0.0000
D(INFLATION_(-1))	0.427888	0.158083	2.706739	0.0104
C	0.491548	0.087019	5.648710	0.0000

R-squared	0.535716	Mean dependent var	-0.003746
Adjusted R-squared	0.509186	S.D. dependent var	0.277475
S.E. of regression	0.194394	Akaike info criterion	-0.362201
Sum squared resid	1.322618	Schwarz criterion	-0.232918
Log likelihood	9.881817	Hannan-Quinn criter.	-0.316203
F-statistic	20.19245	Durbin-Watson stat	1.879948
Prob(F-statistic)	0.000001		

Appendix 18: Inflation unit root test using PP

Null Hypothesis: D(INFLATION_) has a unit root
Exogenous: Constant
Bandwidth: 37 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-17.17254	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.071796
HAC corrected variance (Bartlett kernel)	0.004553

Phillips-Perron Test Equation
Dependent Variable: D(INFLATION_,2)
Method: Least Squares
Date: 01/23/20 Time: 06:51
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(INFLATION_(-1))	-1.211309	0.167597	-7.227516	0.0000
C	-0.003098	0.044661	-0.069358	0.9451

R-squared	0.592008	Mean dependent var	-0.006817
Adjusted R-squared	0.580675	S.D. dependent var	0.425124
S.E. of regression	0.275291	Akaike info criterion	0.309217
Sum squared resid	2.728256	Schwarz criterion	0.395405
Log likelihood	-3.875114	Hannan-Quinn criter.	0.339882
F-statistic	52.23698	Durbin-Watson stat	2.161656
Prob(F-statistic)	0.000000		

Appendix 19: Inflation unit root test using KPSS

Null Hypothesis: D(INFLATION_) is stationary
Exogenous: Constant
Bandwidth: 38 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.450000
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.073667
HAC corrected variance (Bartlett kernel)	0.003305

KPSS Test Equation
Dependent Variable: D(INFLATION_)
Method: Least Squares
Date: 01/23/20 Time: 07:10
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007796	0.044030	-0.177052	0.8604

R-squared	0.000000	Mean dependent var	-0.007796
Adjusted R-squared	0.000000	S.D. dependent var	0.274965
S.E. of regression	0.274965	Akaike info criterion	0.280964
Sum squared resid	2.873027	Schwarz criterion	0.323619
Log likelihood	-4.478791	Hannan-Quinn criter.	0.296268
Durbin-Watson stat	2.328135		

Appendix 20: Inflation unit root test using Ng-Perron

Null Hypothesis: INFLATION_ has a unit root
Exogenous: Constant
Lag length: 1 (Spectral GLS-detrended AR based on SIC, maxlag=9)
Sample: 2009Q1 2018Q4
Included observations: 40

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-50.0889	-4.95870	0.09900	0.60442
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

HAC corrected variance (Spectral GLS-detrended AR)	0.105166

Appendix 21: GDP unit root test using ADF

Null Hypothesis: D(GDP_RATE_) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.604792	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP_RATE_,2)
Method: Least Squares
Date: 01/23/20 Time: 07:40
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP_RATE_(-1))	-0.982152	0.148703	-6.604792	0.0000
C	0.015370	0.075571	0.203387	0.8400

R-squared	0.547871	Mean dependent var	-0.048739
Adjusted R-squared	0.535312	S.D. dependent var	0.677725
S.E. of regression	0.461992	Akaike info criterion	1.344657
Sum squared resid	7.683715	Schwarz criterion	1.430846
Log likelihood	-23.54849	Hannan-Quinn criter.	1.375323
F-statistic	43.62327	Durbin-Watson stat	2.101419
Prob(F-statistic)	0.000000		

Appendix 22: GDP unit root test using PP

Null Hypothesis: GDP_RATE_ has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.168432	0.0022
Test critical values:	1% level	-3.610453	
	5% level	-2.938987	
	10% level	-2.607932	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.170587
HAC corrected variance (Bartlett kernel)	0.274127

Phillips-Perron Test Equation
Dependent Variable: D(GDP_RATE_)
Method: Least Squares
Date: 01/23/20 Time: 07:41
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP_RATE_(-1)	-0.395107	0.094084	-4.199531	0.0002
C	0.879600	0.207874	4.231406	0.0001

R-squared	0.322792	Mean dependent var	0.054510
Adjusted R-squared	0.304489	S.D. dependent var	0.508454
S.E. of regression	0.424037	Akaike info criterion	1.171929
Sum squared resid	6.652879	Schwarz criterion	1.257240
Log likelihood	-20.85262	Hannan-Quinn criter.	1.202538
F-statistic	17.63606	Durbin-Watson stat	1.657946
Prob(F-statistic)	0.000161		

Appendix 23: GDP unit root test using KPPS

Null Hypothesis: GDP_RATE_ is stationary
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.141763
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.511252
HAC corrected variance (Bartlett kernel)	1.252723

KPSS Test Equation
Dependent Variable: GDP_RATE_
Method: Least Squares
Date: 01/23/20 Time: 07:42
Sample: 2009Q1 2018Q4
Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.078904	0.114495	18.15722	0.0000

R-squared	0.000000	Mean dependent var	2.078904
Adjusted R-squared	0.000000	S.D. dependent var	0.724128
S.E. of regression	0.724128	Akaike info criterion	2.216984
Sum squared resid	20.45007	Schwarz criterion	2.259206
Log likelihood	-43.33968	Hannan-Quinn criter.	2.232250
Durbin-Watson stat	0.486055		

Appendix 24: GDP unit root test using Ng-Perron

Null Hypothesis: D(GDP_RATE_) has a unit root
Exogenous: Constant
Lag length: 3 (Spectral GLS-detrended AR based on SIC, maxlag=9)
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-1.32023	-0.63540	0.48128	13.9989
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

HAC corrected variance (Spectral GLS-detrended AR)	0.056639

Appendix 25: Crude oil unit root test using ADF

Null Hypothesis: CRUDEOIL has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.352996	0.0001
Test critical values:	1% level	-3.610453	
	5% level	-2.938987	
	10% level	-2.607932	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CRUDEOIL)
Method: Least Squares
Date: 01/23/20 Time: 07:46
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CRUDEOIL(-1)	-0.922918	0.172412	-5.352996	0.0000
C	0.407382	0.874866	0.465650	0.6442

R-squared	0.436444	Mean dependent var	-0.366923
Adjusted R-squared	0.421213	S.D. dependent var	7.082650
S.E. of regression	5.388341	Akaike info criterion	6.256273
Sum squared resid	1074.266	Schwarz criterion	6.341584
Log likelihood	-119.9973	Hannan-Quinn criter.	6.286881
F-statistic	28.65457	Durbin-Watson stat	1.816781
Prob(F-statistic)	0.000005		

Appendix 26: Crude oil unit root test using PP

Null Hypothesis: D(CRUDEOIL) has a unit root
Exogenous: Constant
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-12.96827	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	38.71015
HAC corrected variance (Bartlett kernel)	13.34970

Phillips-Perron Test Equation
Dependent Variable: D(CRUDEOIL,2)
Method: Least Squares
Date: 01/23/20 Time: 07:47
Sample (adjusted): 2009Q3 2018Q4
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CRUDEOIL(-1))	-1.435788	0.151849	-9.455366	0.0000
C	-0.653785	1.037007	-0.630454	0.5324

R-squared	0.712928	Mean dependent var	-0.558947
Adjusted R-squared	0.704953	S.D. dependent var	11.76814
S.E. of regression	6.392239	Akaike info criterion	6.599242
Sum squared resid	1470.986	Schwarz criterion	6.685431
Log likelihood	-123.3856	Hannan-Quinn criter.	6.629907
F-statistic	89.40395	Durbin-Watson stat	2.110049
Prob(F-statistic)	0.000000		

Appendix 27: Crude oil unit root test using KPSS

Null Hypothesis: D(CRUDEOIL) is stationary
Exogenous: Constant
Bandwidth: 21 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.285515
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	48.87768
HAC corrected variance (Bartlett kernel)	4.388281

KPSS Test Equation
Dependent Variable: D(CRUDEOIL)
Method: Least Squares
Date: 01/23/20 Time: 07:47
Sample (adjusted): 2009Q2 2018Q4
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.366923	1.134132	-0.323528	0.7481

R-squared	0.000000	Mean dependent var	-0.366923
Adjusted R-squared	0.000000	S.D. dependent var	7.082650
S.E. of regression	7.082650	Akaike info criterion	6.778480
Sum squared resid	1906.229	Schwarz criterion	6.821135
Log likelihood	-131.1804	Hannan-Quinn criter.	6.793784
Durbin-Watson stat	2.694307		

Appendix 28: Crude oil unit root test using NG- Perron

Null Hypothesis: CRUDEOIL has a unit root
Exogenous: Constant
Lag length: 0 (Spectral GLS-detrended AR based on SIC, maxlag=9)
Sample: 2009Q1 2018Q4
Included observations: 40

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-19.1727	-2.90868	0.15171	1.92938
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

HAC corrected variance (Spectral GLS-detrended AR)	28.07101

APPENDIX 29: Bounds test and ARDL long run coefficients for model 1

ARDL Long Run Form and Bounds Test
Dependent Variable: D(EMUNLISTED)
Selected Model: ARDL(3, 1, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 10/14/19 Time: 13:55
Sample: 2009Q1 2018Q4
Included observations: 36

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.598816	2.573933	3.340730	0.0033
EMUNLISTED(-1)*	-0.723212	0.131200	-5.512291	0.0000
EMINFLATION(-1)	171.4518	86.58790	1.980090	0.0616
EMGDP(-1)	40.33046	56.02041	0.719924	0.4799
OILPRICE(-1)	-0.377176	0.093484	-4.034675	0.0006
D(EMUNLISTED(-1))	0.211488	0.133898	1.579473	0.1299
D(EMUNLISTED(-2))	0.503362	0.157302	3.199963	0.0045
D(EMINFLATION)	4.986961	73.03896	0.068278	0.9462
D(EMGDP)	35.56971	60.58069	0.587146	0.5637
D(EMGDP(-1))	-67.93709	38.82854	-1.749669	0.0955
D(EMGDP(-2))	-118.1083	38.77069	-3.046329	0.0064
D(EMGDP(-3))	-205.3419	38.98454	-5.267266	0.0000
D(OILPRICE)	0.067085	0.035451	1.892339	0.0730
D(OILPRICE(-1))	0.303935	0.077535	3.919976	0.0008
D(OILPRICE(-2))	0.178941	0.052801	3.388956	0.0029
D(OILPRICE(-3))	0.057660	0.035472	1.625503	0.1197

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMINFLATION	237.0699	134.4797	1.762868	0.0932
EMGDP	55.76573	81.60416	0.683369	0.5022
OILPRICE	-0.521529	0.094708	-5.506723	0.0000
C	11.88976	1.892278	6.283301	0.0000

EC = EMUNLISTED - (237.0699*EMINFLATION + 55.7657*EMGDP -0.5215
*OILPRICE + 11.8898)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	10.33120	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	36		Finite Sample: n=40	
		10%	2.592	3.454
		5%	3.1	4.088
		1%	4.31	5.544
			Finite Sample: n=35	
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

APPENDIX 30: ARDL short run coefficients for Model 1

ARDL Error Correction Regression
Dependent Variable: D(EMUNLISTED)
Selected Model: ARDL(3, 1, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 10/14/19 Time: 13:56
Sample: 2009Q1 2018Q4
Included observations: 36

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EMUNLISTED(-1))	0.211488	0.102069	2.072012	0.0514
D(EMUNLISTED(-2))	0.503362	0.113650	4.429061	0.0003
D(EMINFLATION)	4.986961	52.28705	0.095377	0.9250
D(EMGDP)	35.56971	32.67572	1.088567	0.2893
D(EMGDP(-1))	-67.93709	33.88279	-2.005062	0.0587
D(EMGDP(-2))	-118.1083	33.30650	-3.546103	0.0020
D(EMGDP(-3))	-205.3419	34.86433	-5.889743	0.0000
D(OILPRICE)	0.067085	0.028442	2.358625	0.0286
D(OILPRICE(-1))	0.303935	0.053912	5.637580	0.0000
D(OILPRICE(-2))	0.178941	0.040129	4.459188	0.0002
D(OILPRICE(-3))	0.057660	0.030313	1.902152	0.0717
CointEq(-1)*	-0.723212	0.091858	-7.873197	0.0000

R-squared	0.828063	Mean dependent var	0.166111
Adjusted R-squared	0.749258	S.D. dependent var	1.363859
S.E. of regression	0.682940	Akaike info criterion	2.336382
Sum squared resid	11.19377	Schwarz criterion	2.864222
Log likelihood	-30.05488	Hannan-Quinn criter.	2.520613
Durbin-Watson stat	1.823004		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	10.33120	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

APPENDIX 31: Heteroscedasticity test for ARDL model 1

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.964496	Prob. F(15,20)	0.5201
Obs*R-squared	15.11072	Prob. Chi-Square(15)	0.4435
Scaled explained SS	3.283979	Prob. Chi-Square(15)	0.9993

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/25/20 Time: 04:20
Sample: 2010Q1 2018Q4
Included observations: 36

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.472433	1.297448	-0.364125	0.7196
UNLISTEDINFRA(-1)	0.029401	0.077095	0.381357	0.7070
UNLISTEDINFRA(-2)	-0.023763	0.093426	-0.254355	0.8018
UNLISTEDINFRA(-3)	0.035289	0.079292	0.445055	0.6611
INFLATION_	0.129275	0.368169	0.351130	0.7292
INFLATION_(-1)	-0.049227	0.379551	-0.129698	0.8981
GDP_RATE_	0.125897	0.305370	0.412275	0.6845
GDP_RATE_(-1)	0.046353	0.231874	0.199905	0.8436
GDP_RATE_(-2)	-0.266590	0.219028	-1.217149	0.2377
GDP_RATE_(-3)	0.166574	0.215454	0.773130	0.4485
GDP_RATE_(-4)	0.024467	0.196510	0.124507	0.9022
CRUDEOIL	0.015347	0.017870	0.858851	0.4006
CRUDEOIL(-1)	-0.038602	0.016264	-2.373477	0.0278
CRUDEOIL(-2)	0.012769	0.018909	0.675273	0.5072
CRUDEOIL(-3)	0.008016	0.016653	0.481352	0.6355
CRUDEOIL(-4)	0.009204	0.017880	0.514773	0.6124

R-squared	0.419742	Mean dependent var	0.310938
Adjusted R-squared	-0.015451	S.D. dependent var	0.374228
S.E. of regression	0.377108	Akaike info criterion	1.188533
Sum squared resid	2.844211	Schwarz criterion	1.892319
Log likelihood	-5.393590	Hannan-Quinn criter.	1.434173
F-statistic	0.964496	Durbin-Watson stat	1.984548
Prob(F-statistic)	0.520144		

APPENDIX 32: Autocorrelation test for ARDL model 1

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

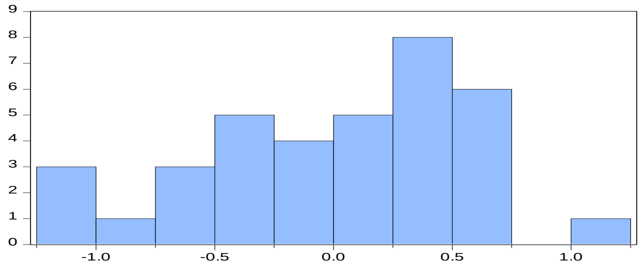
F-statistic	0.451386	Prob. F(2,18)	0.6438
Obs*R-squared	1.719313	Prob. Chi-Square(2)	0.4233

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 01/25/20 Time: 04:22
Sample: 2010Q1 2018Q4
Included observations: 36
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UNLISTEDINFRA(-1)	-0.051737	0.196718	-0.262999	0.7955
UNLISTEDINFRA(-2)	-0.061900	0.223045	-0.277520	0.7845
UNLISTEDINFRA(-3)	0.071255	0.179448	0.397076	0.6960
INFLATION_	0.056318	0.755845	0.074510	0.9414
INFLATION_(-1)	0.093220	0.781005	0.119359	0.9063
GDP_RATE_	0.016324	0.623679	0.026173	0.9794
GDP_RATE_(-1)	0.033845	0.474507	0.071326	0.9439
GDP_RATE_(-2)	0.030278	0.453574	0.066755	0.9475
GDP_RATE_(-3)	0.080849	0.449391	0.179909	0.8592
GDP_RATE_(-4)	0.003517	0.401514	0.008760	0.9931
CRUDEOIL	-0.009112	0.039503	-0.230653	0.8202
CRUDEOIL(-1)	-0.011818	0.035728	-0.330768	0.7446
CRUDEOIL(-2)	-0.006684	0.041138	-0.162467	0.8727
CRUDEOIL(-3)	-0.011834	0.036205	-0.326857	0.7475
CRUDEOIL(-4)	-0.005975	0.037530	-0.159199	0.8753
C	0.186954	2.665798	0.070131	0.9449
RESID(-1)	0.125277	0.318450	0.393395	0.6986
RESID(-2)	0.264374	0.308348	0.857389	0.4025

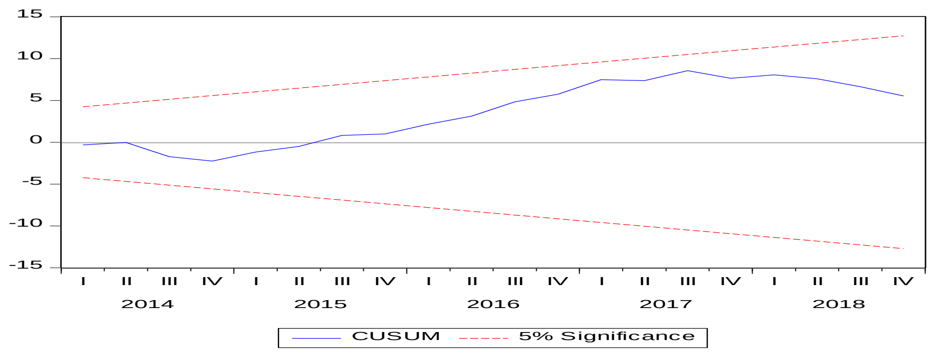
R-squared	0.047759	Mean dependent var	-1.05E-16
Adjusted R-squared	-0.851580	S.D. dependent var	0.565528
S.E. of regression	0.769530	Akaike info criterion	2.620779
Sum squared resid	10.65917	Schwarz criterion	3.412538
Log likelihood	-29.17402	Hannan-Quinn criter.	2.897124
F-statistic	0.053104	Durbin-Watson stat	1.987262
Prob(F-statistic)	1.000000		

APPENDIX 33: Normality test for ARDL model 1



Series: Residuals	
Sample 2010Q1 2018Q4	
Observations 36	
Mean	-2.06e-15
Median	0.071345
Maximum	1.123559
Minimum	-1.214284
Std. Dev.	0.565528
Skewness	-0.326887
Kurtosis	2.408284
Jarque-Bera	1.166322
Probability	0.558131

APPENDIX 34: Stability test for ARDL model 1



APPENDIX 35: Bounds tests and long run coefficients for ARDL model 2

ARDL Long Run Form and Bounds Test
Dependent Variable: D(EMLISTEDINF)
Selected Model: ARDL(5, 4, 2, 5)
Case 2: Restricted Constant and No Trend
Date: 10/14/19 Time: 14:02
Sample: 2009Q1 2018Q4
Included observations: 35

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	11.60938	13.80690	0.840839	0.4136
EMLISTEDINF(-1)*	-1.425236	0.311822	-4.570667	0.0004
EMINFLATION(-1)	-2600.951	3310.312	-0.785712	0.4443
EMGDP(-1)	-132.8925	539.9697	-0.246111	0.8089
OILPRICE(-1)	2.270059	1.571701	1.444332	0.1692
D(EMLISTEDINF(-1))	0.597734	0.261980	2.281597	0.0375
D(EMLISTEDINF(-2))	0.565959	0.269193	2.102426	0.0528
D(EMLISTEDINF(-3))	1.144754	0.302491	3.784420	0.0018
D(EMLISTEDINF(-4))	1.170614	0.302713	3.867072	0.0015
D(EMINFLATION)	-2029.251	1433.316	-1.415773	0.1773
D(EMINFLATION(-1))	35.40187	2584.121	0.013700	0.9893
D(EMINFLATION(-2))	3582.830	2031.919	1.763274	0.0982
D(EMINFLATION(-3))	1648.619	1479.727	1.114137	0.2828
D(EMGDP)	150.5778	926.6645	0.162494	0.8731
D(EMGDP(-1))	-738.9161	520.8951	-1.418551	0.1765
D(OILPRICE)	1.737232	0.646666	2.686443	0.0169
D(OILPRICE(-1))	-0.662220	1.234498	-0.536428	0.5995
D(OILPRICE(-2))	-2.114490	0.943538	-2.241022	0.0406
D(OILPRICE(-3))	-1.860528	0.735001	-2.531329	0.0230
D(OILPRICE(-4))	-0.889757	0.518618	-1.715630	0.1068

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMINFLATION	-1824.926	2416.912	-0.755065	0.4619
EMGDP	-93.24240	374.6265	-0.248894	0.8068
OILPRICE	1.592759	0.952011	1.673048	0.1150
C	8.145581	9.776441	0.833185	0.4178

EC = EMLISTEDINF - (-1824.9262*EMINFLATION -93.2424*EMGDP + 1.5928
*OILPRICE + 8.1456)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	4.769895	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	35		Finite Sample: n=35	
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

APPENDIX 36: Short run coefficients for ARDL model 2

ARDL Error Correction Regression
Dependent Variable: D(LISTEDINFRA)
Selected Model: ARDL(5, 4, 2, 5)
Case 2: Restricted Constant and No Trend
Date: 01/24/20 Time: 13:54
Sample: 2009Q1 2018Q4
Included observations: 35

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LISTEDINFRA(-1))	0.597734	0.225597	2.649566	0.0182
D(LISTEDINFRA(-2))	0.565959	0.236677	2.391274	0.0303
D(LISTEDINFRA(-3))	1.144754	0.257231	4.450291	0.0005
D(LISTEDINFRA(-4))	1.170614	0.258698	4.525017	0.0004
D(INFLATION_)	-20.29251	10.16673	-1.995973	0.0644
D(INFLATION_(-1))	0.354021	10.20507	0.034691	0.9728
D(INFLATION_(-2))	35.82830	10.76485	3.328268	0.0046
D(INFLATION_(-3))	16.48619	9.758843	1.689359	0.1118
D(GDP_RATE_)	1.505778	6.925480	0.217426	0.8308
D(GDP_RATE_(-1))	-7.389161	4.116726	-1.794912	0.0928
D(CRUDEOIL)	1.737232	0.519740	3.342502	0.0045
D(CRUDEOIL(-1))	-0.662220	0.744937	-0.888960	0.3881
D(CRUDEOIL(-2))	-2.114490	0.690291	-3.063187	0.0079
D(CRUDEOIL(-3))	-1.860528	0.566717	-3.282992	0.0050
D(CRUDEOIL(-4))	-0.889756	0.402425	-2.210988	0.0430
CointEq(-1)*	-1.425236	0.259308	-5.496302	0.0001

R-squared	0.764902	Mean dependent var	-0.407214
Adjusted R-squared	0.579298	S.D. dependent var	14.83056
S.E. of regression	9.619326	Akaike info criterion	7.668802
Sum squared resid	1758.097	Schwarz criterion	8.379818
Log likelihood	-118.2040	Hannan-Quinn criter.	7.914245
Durbin-Watson stat	1.954688		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	4.769895	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

APPENDIX 37: Autocorrelation test for ARDL model 2

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	0.071842	Prob. F(2,13)	0.9310
Obs*R-squared	0.382615	Prob. Chi-Square(2)	0.8259

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 01/25/20 Time: 04:25
Sample: 2010Q2 2018Q4
Included observations: 35
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LISTEDINFRA(-1)	0.002978	0.282390	0.010546	0.9917
LISTEDINFRA(-2)	-0.049968	0.301983	-0.165465	0.8711
LISTEDINFRA(-3)	0.044727	0.298476	0.149852	0.8832
LISTEDINFRA(-4)	-0.006668	0.289015	-0.023073	0.9819
LISTEDINFRA(-5)	-0.018130	0.341760	-0.053050	0.9585
INFLATION_	-0.582548	15.84466	-0.036766	0.9712
INFLATION_(-1)	-0.348531	15.59543	-0.022348	0.9825
INFLATION_(-2)	1.065806	18.08741	0.058925	0.9539
INFLATION_(-3)	-1.793689	16.72618	-0.107238	0.9162
INFLATION_(-4)	0.643525	15.94556	0.040358	0.9684
GDP_RATE_	-0.021873	9.902526	-0.002209	0.9983
GDP_RATE_(-1)	0.275924	9.352670	0.029502	0.9769
GDP_RATE_(-2)	-0.095781	5.575856	-0.017178	0.9866
CRUDEOIL	0.052668	0.705440	0.074660	0.9416
CRUDEOIL(-1)	-0.024459	0.682792	-0.035822	0.9720
CRUDEOIL(-2)	-0.011721	0.744711	-0.015739	0.9877
CRUDEOIL(-3)	-0.003505	0.522370	-0.006710	0.9947
CRUDEOIL(-4)	-0.010774	0.498604	-0.021609	0.9831
CRUDEOIL(-5)	0.004035	0.573385	0.007038	0.9945
C	-0.014916	14.85806	-0.001004	0.9992
RESID(-1)	0.006673	0.396015	0.016850	0.9868
RESID(-2)	0.147983	0.404744	0.365620	0.7205

R-squared	0.010932	Mean dependent var	9.77E-16
Adjusted R-squared	-1.586794	S.D. dependent var	7.190879
S.E. of regression	11.56546	Akaike info criterion	8.000667
Sum squared resid	1738.878	Schwarz criterion	8.978315
Log likelihood	-118.0117	Hannan-Quinn criter.	8.338151
F-statistic	0.006842	Durbin-Watson stat	1.922941
Prob(F-statistic)	1.000000		

APPENDIX 38: Heteroscedasticity test for ARDL model 2

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

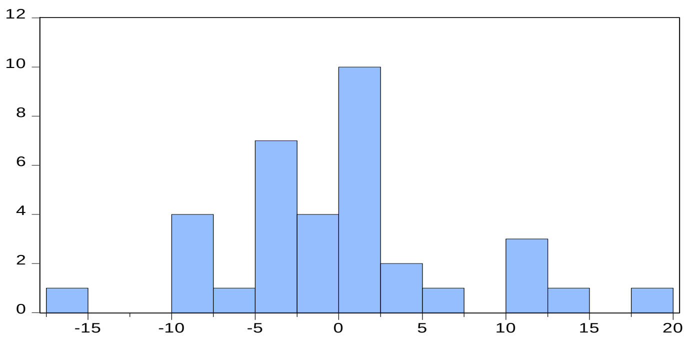
F-statistic	0.904963	Prob. F(19,15)	0.5875
Obs*R-squared	18.69277	Prob. Chi-Square(19)	0.4767
Scaled explained SS	4.410019	Prob. Chi-Square(19)	0.9998

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/25/20 Time: 04:26
Sample: 2010Q2 2018Q4
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.00900	107.0570	0.186901	0.8542
LISTEDINFRA(-1)	-2.166454	1.526980	-1.418784	0.1764
LISTEDINFRA(-2)	0.044897	1.727562	0.025989	0.9796
LISTEDINFRA(-3)	2.982508	1.972530	1.512022	0.1513
LISTEDINFRA(-4)	-2.589691	2.064460	-1.254416	0.2289
LISTEDINFRA(-5)	2.664544	2.347201	1.135201	0.2741
INFLATION_	20.08884	111.1375	0.180757	0.8590
INFLATION_(-1)	43.98696	112.1366	0.392262	0.7004
INFLATION_(-2)	18.30087	128.6117	0.142295	0.8887
INFLATION_(-3)	0.566772	114.8370	0.004935	0.9961
INFLATION_(-4)	173.9951	114.7362	1.516480	0.1502
GDP_RATE_	69.82014	71.85241	0.971716	0.3466
GDP_RATE_(-1)	-68.77867	67.60675	-1.017334	0.3251
GDP_RATE_(-2)	-31.84525	40.38955	-0.788453	0.4427
CRUDEOIL	3.537436	5.014170	0.705488	0.4913
CRUDEOIL(-1)	1.200646	4.904947	0.244783	0.8099
CRUDEOIL(-2)	4.064717	5.386067	0.754672	0.4621
CRUDEOIL(-3)	-0.402359	3.788852	-0.106196	0.9168
CRUDEOIL(-4)	-0.770707	3.599511	-0.214114	0.8333
CRUDEOIL(-5)	-2.304121	4.021300	-0.572979	0.5751

R-squared	0.534079	Mean dependent var	50.23135
Adjusted R-squared	-0.056088	S.D. dependent var	81.68544
S.E. of regression	83.94496	Akaike info criterion	11.99376
Sum squared resid	105701.3	Schwarz criterion	12.88253
Log likelihood	-189.8908	Hannan-Quinn criter.	12.30056
F-statistic	0.904963	Durbin-Watson stat	2.223671
Prob(F-statistic)	0.587494		

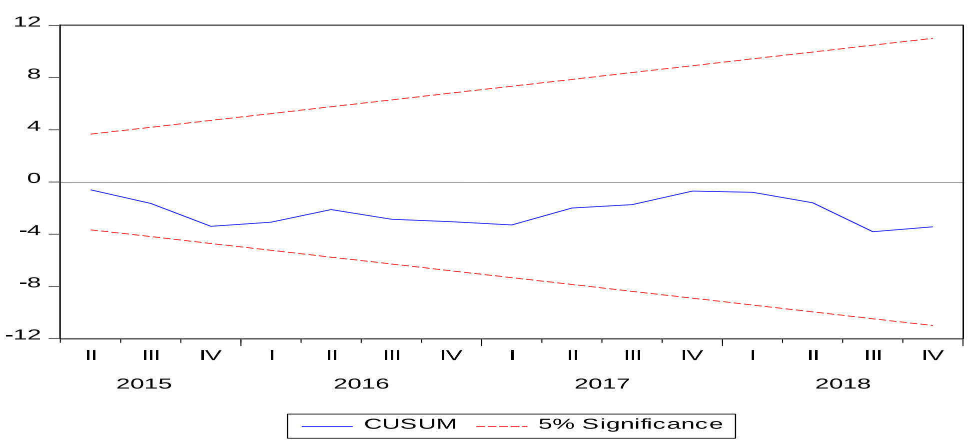
APPENDIX 39: Normality test for ARDL model 2



Series: Residuals
Sample 2010Q2 2018Q4
Observations 35

Mean	1.25e-14
Median	0.068967
Maximum	18.66356
Minimum	-17.03900
Std. Dev.	7.190879
Skewness	0.350032
Kurtosis	3.568919
Jarque-Bera	1.186729
Probability	0.552465

APPENDIX 40: Stability test for ARDL model 2



APPENDIX 41: Bounds test and long run coefficients for ARDL model 3

ARDL Long Run Form and Bounds Test
Dependent Variable: D(EMREAL)
Selected Model: ARDL(4, 0, 5, 0)
Case 2: Restricted Constant and No Trend
Date: 10/14/19 Time: 14:12
Sample: 2009Q1 2018Q4
Included observations: 35

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.278137	3.668484	-0.075818	0.9402
EMREAL(-1)*	-1.458318	0.371375	-3.926805	0.0007
EMINFLATION**	131.6341	260.0492	0.506189	0.6178
EMGDP(-1)	-0.850905	158.2970	-0.005375	0.9958
OILPRICE**	0.047596	0.114805	0.414583	0.6825
D(EMREAL(-1))	0.477832	0.312574	1.528701	0.1406
D(EMREAL(-2))	0.477379	0.228474	2.089426	0.0484
D(EMREAL(-3))	0.335347	0.155172	2.161128	0.0418
D(EMGDP)	-207.8121	234.4081	-0.886540	0.3849
D(EMGDP(-1))	272.1652	139.2468	1.954552	0.0635
D(EMGDP(-2))	297.8753	131.3049	2.268577	0.0335
D(EMGDP(-3))	-74.56248	148.1975	-0.503129	0.6199
D(EMGDP(-4))	-276.2603	143.9422	-1.919245	0.0680

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMINFLATION	90.26434	180.4634	0.500181	0.6219
EMGDP	-0.583484	108.5179	-0.005377	0.9958
OILPRICE	0.032638	0.077019	0.423759	0.6759
C	-0.190724	2.526350	-0.075494	0.9405

EC = EMREAL - (90.2643*EMINFLATION -0.5835*EMGDP + 0.0326*OILPRICE - 0.1907)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	3.311650	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	35		Finite Sample: n=35	
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

APPENDIX 42: Short run coefficients for ARDL model 3

ARDL Error Correction Regression
Dependent Variable: D(EMREAL)
Selected Model: ARDL(4, 0, 5, 0)
Case 2: Restricted Constant and No Trend
Date: 01/24/20 Time: 13:56
Sample: 2009Q1 2018Q4
Included observations: 35

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EMREAL(-1))	0.477832	0.280887	1.701150	0.1030
D(EMREAL(-2))	0.477379	0.206734	2.309149	0.0307
D(EMREAL(-3))	0.335347	0.138958	2.413299	0.0246
D(GDP_RATE_)	-2.078122	1.952152	-1.064529	0.2986
D(GDP_RATE_(-1))	2.721651	1.238342	2.197818	0.0388
D(GDP_RATE_(-2))	2.978754	1.037031	2.872386	0.0088
D(GDP_RATE_(-3))	-0.745624	1.078042	-0.691647	0.4964
D(GDP_RATE_(-4))	-2.762603	1.180047	-2.341097	0.0287
CointEq(-1)*	-1.458318	0.329663	-4.423668	0.0002

R-squared	0.734962	Mean dependent var	0.022300
Adjusted R-squared	0.653412	S.D. dependent var	4.608532
S.E. of regression	2.713123	Akaike info criterion	5.051112
Sum squared resid	191.3869	Schwarz criterion	5.451059
Log likelihood	-79.39446	Hannan-Quinn criter.	5.189174
Durbin-Watson stat	2.212513		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	3.311649	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

APPENDIX 43: Heteroscedasticity test for ARDL model 3

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.371262	Prob. F(12,22)	0.9604
Obs*R-squared	5.894132	Prob. Chi-Square(12)	0.9213
Scaled explained SS	2.190717	Prob. Chi-Square(12)	0.9991

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/25/20 Time: 04:29
Sample: 2010Q2 2018Q4
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.634562	10.73022	-0.245527	0.8083
EMREAL(-1)	0.486880	0.509698	0.955232	0.3498
EMREAL(-2)	-0.263893	0.526727	-0.501005	0.6213
EMREAL(-3)	0.177905	0.477251	0.372769	0.7129
EMREAL(-4)	0.135647	0.453874	0.298865	0.7678
INFLATION	4.126505	7.606369	0.542507	0.5929
GDP_RATE_	6.182895	6.856375	0.901773	0.3769
GDP_RATE_(-1)	-5.780871	7.516841	-0.769056	0.4500
GDP_RATE_(-2)	-1.822977	5.181124	-0.351850	0.7283
GDP_RATE_(-3)	-1.549179	4.799003	-0.322813	0.7499
GDP_RATE_(-4)	8.098220	5.225251	1.549824	0.1355
GDP_RATE_(-5)	-2.028684	4.210272	-0.481841	0.6347
CRUDEOIL	-0.063453	0.335800	-0.188961	0.8519

R-squared	0.168404	Mean dependent var	5.468198
Adjusted R-squared	-0.285194	S.D. dependent var	7.609961
S.E. of regression	8.627139	Akaike info criterion	7.426254
Sum squared resid	1637.405	Schwarz criterion	8.003955
Log likelihood	-116.9595	Hannan-Quinn criter.	7.625677
F-statistic	0.371262	Durbin-Watson stat	2.024153
Prob(F-statistic)	0.960450		

APPENDIX 44: Autocorrelation test for model 3

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

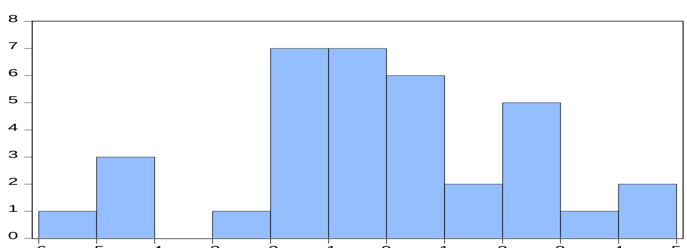
F-statistic	1.752413	Prob. F(2,20)	0.1989
Obs*R-squared	5.218881	Prob. Chi-Square(2)	0.0736

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 01/25/20 Time: 04:29
Sample: 2010Q2 2018Q4
Included observations: 35
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMREAL(-1)	0.258319	0.300913	0.858450	0.4008
EMREAL(-2)	0.359020	0.282488	1.270924	0.2183
EMREAL(-3)	0.008251	0.160052	0.051555	0.9594
EMREAL(-4)	0.051605	0.152646	0.338069	0.7388
INFLATION_	-1.799069	2.760506	-0.651717	0.5220
GDP_RATE_	0.721837	2.443889	0.295364	0.7708
GDP_RATE_(-1)	0.148606	2.669029	0.055678	0.9562
GDP_RATE_(-2)	0.013576	1.716545	0.007909	0.9938
GDP_RATE_(-3)	-1.127065	1.809616	-0.622820	0.5404
GDP_RATE_(-4)	0.241754	1.886179	0.128171	0.8993
GDP_RATE_(-5)	1.097836	1.519215	0.722634	0.4783
CRUDEOIL	0.072423	0.117628	0.615693	0.5450
C	-1.619223	3.657698	-0.442689	0.6627
RESID(-1)	-0.463343	0.388222	-1.193500	0.2466
RESID(-2)	-0.610127	0.379454	-1.607908	0.1235

R-squared	0.149111	Mean dependent var	-2.06E-15
Adjusted R-squared	-0.446512	S.D. dependent var	2.372557
S.E. of regression	2.853498	Akaike info criterion	5.232496
Sum squared resid	162.8491	Schwarz criterion	5.899073
Log likelihood	-76.56867	Hannan-Quinn criter.	5.462598
F-statistic	0.250345	Durbin-Watson stat	2.103885
Prob(F-statistic)	0.994599		

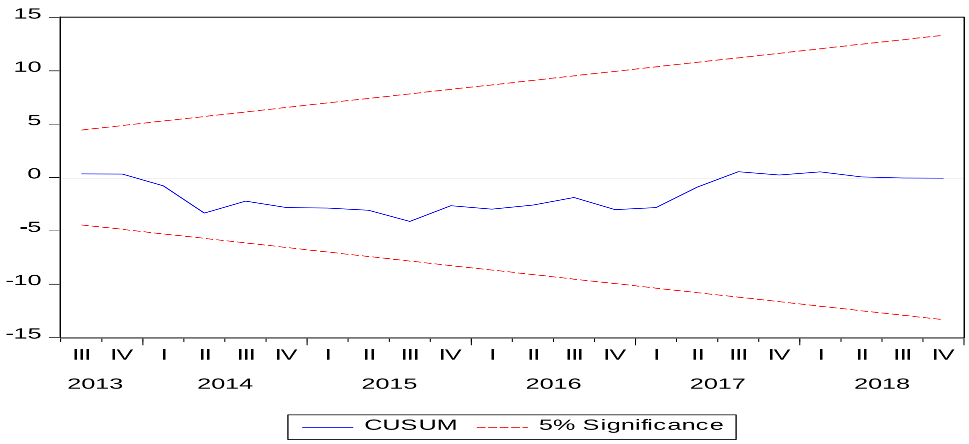
APPENDIX 45: Normality test for ARDL model 3



Series: Residuals
Sample 2010Q2 2018Q4
Observations 35

Mean	-2.06e-15
Median	-0.109452
Maximum	4.815482
Minimum	-5.182637
Std. Dev.	2.372557
Skewness	-0.108963
Kurtosis	2.881426
Jarque-Bera	0.089762
Probability	0.956111

APPENDIX 46: Stability test for ARDL model 3



APPENDIX 47: Bounds test and long run coefficients ARDL model 4

ARDL Long Run Form and Bounds Test
Dependent Variable: D(EMEQUITY)
Selected Model: ARDL(1, 0, 5, 0)
Case 2: Restricted Constant and No Trend
Date: 10/14/19 Time: 14:16
Sample: 2009Q1 2018Q4
Included observations: 35

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.477509	2.641483	0.180773	0.8580
EMEQUITY(-1)*	-1.165854	0.160987	-7.241934	0.0000
EMINFLATION**	291.5550	186.3103	1.564889	0.1302
EMGDP(-1)	-70.64750	113.4796	-0.622557	0.5392
OILPRICE**	0.166500	0.080424	2.070273	0.0489
D(EMGDP)	-324.0053	159.2829	-2.034150	0.0527
D(EMGDP(-1))	119.5116	91.79748	1.301905	0.2048
D(EMGDP(-2))	330.7207	94.45625	3.501311	0.0018
D(EMGDP(-3))	113.1427	115.7772	0.977245	0.3378
D(EMGDP(-4))	-210.8577	95.74817	-2.202212	0.0371

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMINFLATION	250.0786	163.2694	1.531693	0.1382
EMGDP	-60.59724	95.32785	-0.635672	0.5308
OILPRICE	0.142814	0.069622	2.051281	0.0509
C	0.409579	2.251334	0.181927	0.8571

EC = EMEQUITY - (250.0786*EMINFLATION -60.5972*EMGDP + 0.1428
*OILPRICE + 0.4096)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	11.99212	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	35		Finite Sample: n=35	
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

APPENDIX 48: Short run coefficients ARDL model 4

ARDL Error Correction Regression
Dependent Variable: D(EMALLSTOCK)
Selected Model: ARDL(1, 0, 5, 0)
Case 2: Restricted Constant and No Trend
Date: 01/24/20 Time: 13:57
Sample: 2009Q1 2018Q4
Included observations: 35

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP_RATE_)	-3.240054	1.315753	-2.462510	0.0210
D(GDP_RATE_(-1))	1.195115	0.810072	1.475320	0.1526
D(GDP_RATE_(-2))	3.307207	0.743284	4.449456	0.0002
D(GDP_RATE_(-3))	1.131427	0.843584	1.341214	0.1919
D(GDP_RATE_(-4))	-2.108577	0.777413	-2.712299	0.0119
CointEq(-1)*	-1.165854	0.139792	-8.339922	0.0000

R-squared	0.808099	Mean dependent var	-0.097143
Adjusted R-squared	0.775012	S.D. dependent var	4.167386
S.E. of regression	1.976712	Akaike info criterion	4.355551
Sum squared resid	113.3143	Schwarz criterion	4.622183
Log likelihood	-70.22215	Hannan-Quinn criter.	4.447592
Durbin-Watson stat	1.973506		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	11.99212	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

APPENDIX 49: Heteroscedasticity test for ADRL model 4

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.150820	Prob. F(9,25)	0.3665
Obs*R-squared	10.25269	Prob. Chi-Square(9)	0.3304
Scaled explained SS	6.957360	Prob. Chi-Square(9)	0.6416

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/25/20 Time: 04:31
Sample: 2010Q2 2018Q4
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.39211	6.518272	1.594305	0.1234
EMALLSTOCK(-1)	0.230961	0.397259	0.581387	0.5662
INFLATION_	-8.074494	4.597498	-1.756280	0.0913
GDP_RATE_	2.587414	3.930555	0.658282	0.5164
GDP_RATE_(-1)	-4.975908	4.478793	-1.110993	0.2771
GDP_RATE_(-2)	-1.316800	2.948634	-0.446580	0.6590
GDP_RATE_(-3)	0.600061	3.059742	0.196115	0.8461
GDP_RATE_(-4)	4.267939	2.936250	1.453534	0.1585
GDP_RATE_(-5)	-3.018925	2.362736	-1.277725	0.2131
CRUDEOIL	-0.118199	0.198459	-0.595581	0.5568

R-squared	0.292934	Mean dependent var	3.237551
Adjusted R-squared	0.038390	S.D. dependent var	5.357443
S.E. of regression	5.253600	Akaike info criterion	6.390661
Sum squared resid	690.0079	Schwarz criterion	6.835046
Log likelihood	-101.8366	Hannan-Quinn criter.	6.544062
F-statistic	1.150820	Durbin-Watson stat	2.172351
Prob(F-statistic)	0.366517		

APPENDIX 50: Autocorrelation test for ARDL model 4

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

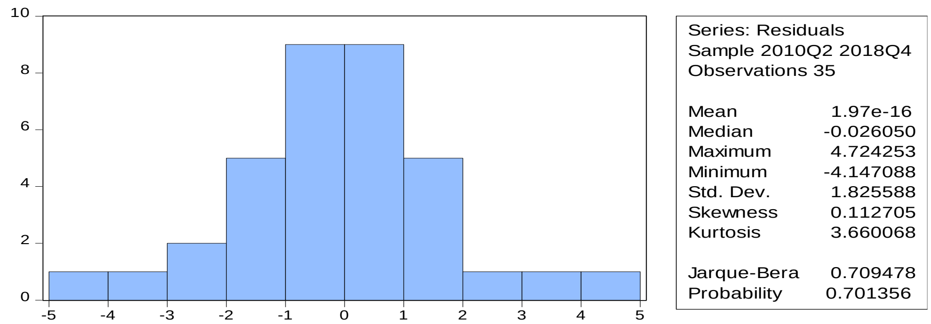
F-statistic	0.156748	Prob. F(2,23)	0.8558
Obs*R-squared	0.470644	Prob. Chi-Square(2)	0.7903

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 01/25/20 Time: 04:32
Sample: 2010Q2 2018Q4
Included observations: 35
Presample missing value lagged residuals set to zero.

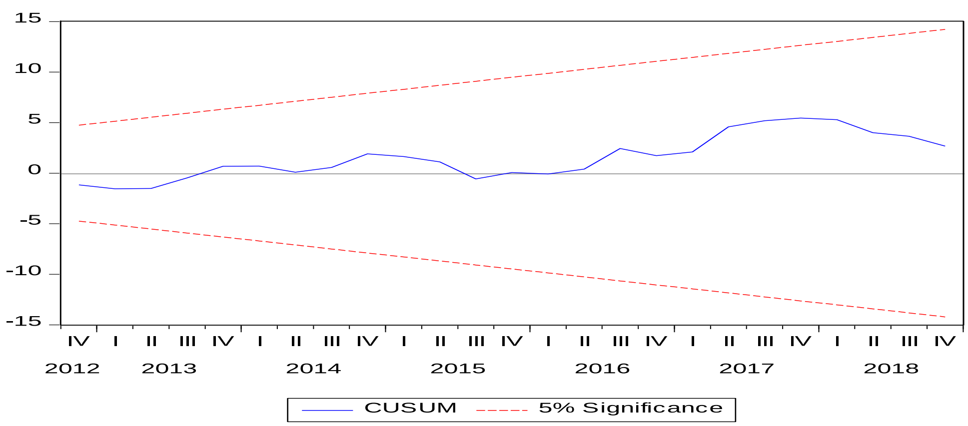
Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMALLSTOCK(-1)	-0.008046	0.267214	-0.030111	0.9762
INFLATION	0.138362	1.996454	0.069304	0.9453
GDP_RATE	0.282869	1.753023	0.161360	0.8732
GDP_RATE_(-1)	-0.335335	2.133350	-0.157187	0.8765
GDP_RATE_(-2)	-0.001051	1.279474	-0.000822	0.9994
GDP_RATE_(-3)	0.066692	1.508385	0.044214	0.9651
GDP_RATE_(-4)	0.050893	1.306280	0.038960	0.9693
GDP_RATE_(-5)	-0.069806	1.076754	-0.064830	0.9489
CRUDEOIL	0.007886	0.089819	0.087799	0.9308
C	-0.017094	2.753036	-0.006209	0.9951
RESID(-1)	0.000124	0.356449	0.000347	0.9997
RESID(-2)	-0.127110	0.227301	-0.559216	0.5814

R-squared	0.013447	Mean dependent var	1.97E-16
Adjusted R-squared	-0.458383	S.D. dependent var	1.825588
S.E. of regression	2.204645	Akaike info criterion	4.684870
Sum squared resid	111.7906	Schwarz criterion	5.218133
Log likelihood	-69.98523	Hannan-Quinn criter.	4.868952
F-statistic	0.028500	Durbin-Watson stat	1.950807
Prob(F-statistic)	1.000000		

APPENDIX 51: Normality test for ARDL model 4



APPENDIX 51: Stability test for model 4



APPENDIX 53: NARDL coefficients for Model 1

_dy	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_y						
L1.	-.3072176	.0950967	-3.23	0.003	-.503073	-.1113622
_x1p						
L1.	-.7530016	2.210459	-0.34	0.736	-5.305527	3.799524
_x1n						
L1.	-.6345882	2.216022	-0.29	0.777	-5.198571	3.929395
_dy						
L1.	-.0345906	.2127906	-0.16	0.872	-.4728411	.4036599
L2.	.2663207	.1935894	1.38	0.181	-.1323842	.6650255
_dx1p						
--.	1.786513	1.546407	1.16	0.259	-1.398372	4.971398
L1.	1.848402	2.510444	0.74	0.468	-3.321954	7.018759
_dx1n						
--.	-2.921155	1.855801	-1.57	0.128	-6.743249	.900938
L1.	-1.846586	1.530048	-1.21	0.239	-4.99778	1.304607
gdprate	-.3986823	.8056873	-0.49	0.625	-2.058026	1.260662
goilprice	.0801614	.0527197	1.52	0.141	-.0284168	.1887396
_cons	4.547652	2.906745	1.56	0.130	-1.438902	10.53421

Asymmetry statistics:

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	coef.	F-stat	P>F	coef.	F-stat	P>F
eminfl	-2.451	.1137	0.739	2.066	.08081	0.779
	Long-run asymmetry			Short-run asymmetry		
		F-stat	P>F		F-stat	P>F
eminfl		.2963	0.591		5.746	0.024

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Cointegration test statistics:		
	t_BDM =	-3.2306
	F_PSS =	3.7804

Model diagnostics	stat.	p-value
Portmanteau test up to lag 16 (chi2)	14.21	0.5834
Breusch/Pagan heteroskedasticity test (chi2)	.01506	0.9023
Ramsey RESET test (F)	2.359	0.0992
Jarque-Bera test on normality (chi2)	4.992	0.0824

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Appendix 54: NARDL coefficients for model 2

_dy	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_y						
L1.	-1.188126	.309995	-3.83	0.001	-1.842158	-.5340933
_x1p						
L1.	-13.03922	39.01466	-0.33	0.742	-95.35296	69.27451
_x1n						
L1.	-14.30805	38.5336	-0.37	0.715	-95.60683	66.99073
_dy						
L1.	.5087997	.2816412	1.81	0.089	-.0854114	1.103011
L2.	.2421699	.2810029	0.86	0.401	-.3506944	.8350342
L3.	.85244	.2846604	2.99	0.008	.2518591	1.453021
L4.	.6628634	.3317492	2.00	0.062	-.0370662	1.362793
_dx1p						
--.	-4.756451	24.68136	-0.19	0.849	-56.82958	47.31667
L1.	-5.985641	36.83479	-0.16	0.873	-83.70026	71.72898
L2.	37.85848	31.42558	1.20	0.245	-28.44369	104.1607
L3.	-27.9763	26.23591	-1.07	0.301	-83.32924	27.37663
_dx1n						
--.	-30.26375	28.06781	-1.08	0.296	-89.48166	28.95416
L1.	-20.62358	31.11359	-0.66	0.516	-86.26751	45.02035
L2.	-14.76982	22.42349	-0.66	0.519	-62.07925	32.53961
L3.	9.038024	15.45961	0.58	0.566	-23.57891	41.65496
gdprate	3.097476	7.153613	0.43	0.670	-11.99533	18.19028
goilprice	1.964552	.7859306	2.50	0.023	.3063831	3.62272
_cons	-16.25136	23.39207	-0.69	0.497	-65.60432	33.1016

Asymmetry statistics:

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	coef.	F-stat	P>F	coef.	F-stat	P>F
eminfl	-10.975	.1124	0.742	12.043	.1393	0.714
	Long-run asymmetry			Short-run asymmetry		
		F-stat	P>F		F-stat	P>F
eminfl		.1655	0.689		.9783	0.336

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Cointegration test statistics:		
	t_BDM =	-3.8327
	F_PSS =	5.0168

Model diagnostics	stat.	p-value
Portmanteau test up to lag 15 (chi2)	11.31	0.7301
Breusch/Pagan heteroskedasticity test (chi2)	3.621	0.0571
Ramsey RESET test (F)	1.254	0.3278
Jarque-Bera test on normality (chi2)	.189	0.9098

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APPENDIX 55: NARDL coefficients for model 3

_dy	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_y						
L1.	-1.416754	.6267721	-2.26	0.035	-2.720198	-.1133105
_x1p						
L1.	-.6671711	8.611228	-0.08	0.939	-18.5752	17.24086
_x1n						
L1.	-.9392494	8.531981	-0.11	0.913	-18.68248	16.80398
_dy						
L1.	.3941539	.479751	0.82	0.421	-.6035429	1.391851
L2.	.3105064	.3713666	0.84	0.413	-.4617927	1.082806
L3.	.2247475	.2679267	0.84	0.411	-.3324366	.7819316
L4.	-.0998961	.1846657	-0.54	0.594	-.4839295	.2841374
_dx1p						
--.	-3.839118	5.461745	-0.70	0.490	-15.19744	7.519204
L1.	9.249451	8.650124	1.07	0.297	-8.739466	27.23837
_dx1n						
--.	7.544547	6.460406	1.17	0.256	-5.890603	20.9797
L1.	-.4250637	4.484524	-0.09	0.925	-9.751143	8.901015
gdprate	.5731943	1.934079	0.30	0.770	-3.448944	4.595332
goilprice	-.0309387	.1604625	-0.19	0.849	-.3646387	.3027614
_cons	-1.539719	5.881673	-0.26	0.796	-13.77133	10.69189

Asymmetry statistics:

Exog. var.	Long-run effect [+] coef.	F-stat	P>F	Long-run effect [-] coef.	F-stat	P>F
eminfl	-0.471	.005809	0.940	0.663	.01158	0.915

	Long-run asymmetry F-stat	P>F	Short-run asymmetry F-stat	P>F
eminfl	.1209	0.731	.0192	0.891

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Cointegration test statistics: t_BDM = -2.2604
F_PSS = 2.2618

Model diagnostics	stat.	p-value
Portmanteau test up to lag 15 (chi2)	6.399	0.9722
Breusch/Pagan heteroskedasticity test (chi2)	1.747	0.1863
Ramsey RESET test (F)	1.205	0.3363
Jarque-Bera test on normality (chi2)	.02736	0.9864

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APPENDIX 56: NARDL coefficients for model 4

_dy	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_y						
L1.	-1.010283	.2118549	-4.77	0.000	-1.444974	-.5755929
_x1p						
L1.	1.089721	5.481524	0.20	0.844	-10.15744	12.33688
_x1n						
L1.	1.401424	5.528723	0.25	0.802	-9.942579	12.74543
_dy						
L1.	.1452465	.1463821	0.99	0.330	-.1551048	.4455978
_dx1p						
--.	-1.714031	3.575082	-0.48	0.635	-9.049494	5.621432
L1.	5.939883	5.645726	1.05	0.302	-5.644191	17.52396
_dx1n						
--.	10.79566	4.446343	2.43	0.022	1.672517	19.9188
L1.	-4.223708	3.376082	-1.25	0.222	-11.15086	2.703441
gdprate	-.3799727	.9400687	-0.40	0.689	-2.308834	1.548889
goilprice	.1246553	.1172208	1.06	0.297	-.115862	.3651726
_cons	2.120316	3.097253	0.68	0.499	-4.234723	8.475354

Asymmetry statistics:

Exog. var.	Long-run effect [+] coef.	F-stat	P>F	Long-run effect [-] coef.	F-stat	P>F
eminfl	1.079	.04051	0.842	-1.387	.06651	0.798

	Long-run asymmetry F-stat	P>F	Short-run asymmetry F-stat	P>F
eminfl	.509	0.482	.08249	0.776

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Cointegration test statistics: t_BDM = -4.7688
F_PSS = 8.9684

Model diagnostics	stat.	p-value
Portmanteau test up to lag 17 (chi2)	17.64	0.4117
Breusch/Pagan heteroskedasticity test (chi2)	2.588	0.1077
Ramsey RESET test (F)	4.533	0.0118
Jarque-Bera test on normality (chi2)	.4401	0.8025

.

APPENDIX 57: Cross Section Dependence (CSD) test for emerging market general stock

Cross-Section Dependence Test
Series: COMPOSITE STOCK
Null hypothesis: No cross-section dependence (correlation)
Sample: 2009M01 2019M06
Periods included: 126
Cross-sections included: 4
Total panel observations: 504
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	756.0000	6	0.0000
Pesaran scaled LM	216.5064		0.0000
Bias-corrected scaled LM	216.4904		0.0000
Pesaran CD	27.49545		0.0000

APPENDIX 58: CSD test for crude oil

Cross-Section Dependence Test
Series: CRUDE OIL
Null hypothesis: No cross-section dependence (correlation)
Sample: 2009M01 2019M06
Periods included: 126
Cross-sections included: 4
Total panel observations: 504
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	756.0000	6	0.0000
Pesaran scaled LM	216.5064		0.0000
Bias-corrected scaled LM	216.4904		0.0000
Pesaran CD	27.49545		0.0000

APPENDIX 59: CSD test for inflation

Cross-Section Dependence Test
Series: INFLATION
Null hypothesis: No cross-section dependence (correlation)
Sample: 2009M01 2019M06
Periods included: 126
Cross-sections included: 4
Total panel observations: 504
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	756.0000	6	0.0000
Pesaran scaled LM	216.5064		0.0000
Bias-corrected scaled LM	216.4904		0.0000
Pesaran CD	27.49545		0.0000

APPENDIX 60: CSD test for GDP

Cross-Section Dependence Test
Series: GDP
Null hypothesis: No cross-section dependence (correlation)
Sample: 2009M01 2019M06
Periods included: 126
Cross-sections included: 4
Total panel observations: 504
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	756.0000	6	0.0000
Pesaran scaled LM	216.5064		0.0000
Bias-corrected scaled LM	216.4904		0.0000
Pesaran CD	27.49545		0.0000

APPENDIX 61: CSD test for infrastructure

Cross-Section Dependence Test
Series: INFRASTRUCTURE
Null hypothesis: No cross-section dependence (correlation)
Sample: 2009M01 2019M06
Periods included: 46
Cross-sections included: 4
Total panel observations: 184
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	276.0000	6	0.0000
Pesaran scaled LM	77.94229		0.0000
Bias-corrected scaled LM	77.89784		0.0000
Pesaran CD	16.61325		0.0000

APPENDIX 62: CSD test for real estate

Cross-Section Dependence Test
Series: REAL_ESTATE
Null hypothesis: No cross-section dependence (correlation)
Sample: 2009M01 2019M06
Periods included: 126
Cross-sections included: 4
Total panel observations: 504
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	756.0000	6	0.0000
Pesaran scaled LM	216.5064		0.0000
Bias-corrected scaled LM	216.4904		0.0000
Pesaran CD	27.49545		0.0000

APPENDIX 63: IPS unit root test for emerging markets composite stock

xtunitroot ips compositestock	
Im-Pesaran-Shin unit-root test for	compositestock
Ho: All panels contain unit roots	Number of panels = 4
Ha: Some panels are stationary	Number of periods = 126
AR parameter: Panel-specific	Asymptotics: T,N -> Infinity
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: No lags included	
Fixed-N exact critical values	
Statistic	p-value 1% 5% 10%
t-bar -10.1674	-2.400 -2.150 -2.010
t-tilde-bar -7.5229	
Z-t-tilde-bar -18.453	0.0000

APPENDIX 64: IPS unit root test for real estate

xtunitroot ips realestate	
Im-Pesaran-Shin unit-root test for	realestate
Ho: All panels contain unit roots	Number of panels = 4
Ha: Some panels are stationary	Avg. number of periods = 122.75
AR parameter: Panel-specific	Asymptotics: T,N -> Infinity
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: No lags included	
Fixed-N exact critical values	
Statistic	p-value 1% 5% 10%
t-bar -9.8318	(Not available)
t-tilde-bar -7.3397	
Z-t-tilde-bar -6.052	0.0000

APPENDIX 65: IPS unit root test for GDP

xtunitroot ips d.gdp		
Im-Pesaran-Shin unit-root test for	D.gdp	
Ho: All panels contain unit roots	Number of panels = 4	
Ha: Some panels are stationary	Number of periods = 125	
AR parameter: Panel-specific	Asymptotics: T,N -> Infinity	
Panel means: Included	sequentially	
Time trend: Not included		
ADF regressions: No lags included		
	Fixed-N exact critical values	
Statistic	p-value	1% 5% 10%
t-bar -11.0922	-2.400 -2.150 -2.010	
t-tilde-bar -7.8587		
Z-t-tilde-bar -7.435	0.0000	

APPENDIX 66: IPS unit root test for crude oil

xtunitroot ips crudeoil		
Im-Pesaran-Shin unit-root test for	crudeoil	
Ho: All panels contain unit roots	Number of panels = 4	
Ha: Some panels are stationary	Avg. number of periods = 124.75	
AR parameter: Panel-specific	Asymptotics: T,N -> Infinity	
Panel means: Included	sequentially	
Time trend: Not included		
ADF regressions: No lags included		
	Fixed-N exact critical values	
Statistic	p-value	1% 5% 10%
t-bar -8.5807	(Not available)	
t-tilde-bar -6.8006		
Z-t-tilde-bar -12.983	0.0000	

APPENDIX 67: IPS unit root test for infrastructure

xtunitroot ips d.infrastructure	
Im-Pesaran-Shin unit-root test for	D.infrastructure
Ho: All panels contain unit roots	Number of panels = 4
Ha: Some panels are stationary	Avg. number of periods = 99.75
AR parameter: Panel-specific	Asymptotics: T,N -> Infinity
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: No lags included	
Fixed-N exact critical values	
Statistic	p-value 1% 5% 10%
t-bar -15.2918	(Not available)
t-tilde-bar -8.1885	
Z-t-tilde-bar -7.916	0.0000

APPENDIX 68: IPS unit root test for inflation

xtunitroot ips d.inflation	
Im-Pesaran-Shin unit-root test for	D.inflation
Ho: All panels contain unit roots	Number of panels = 4
Ha: Some panels are stationary	Number of periods = 125
AR parameter: Panel-specific	Asymptotics: T,N -> Infinity
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: No lags included	

Fixed-N exact critical values	
Statistic	p-value 1% 5% 10%
t-bar -14.4898	-2.400 -2.150 -2.010
t-tilde-bar -8.7431	
Z-t-tilde-bar -9.7612	0.0000

APPENDIX 69: PESCADF unit root test for GDP

pescadf d.gdp, lags(3)				
Pesaran's CADF test for D.gdp				
Cross-sectional average in first period	extracted	and extreme	t-values	truncated
Deterministics chosen: constant				
t-bar test, N,T = (4,125) Obs =	484			
Augmented by 3 lags (average)				
t-bar cv10 cv5 cv1	Z[t-bar]	P-value		
2.610 -2.210 -2.320 -2.530	-3.942	0.000		

APPENDIX 70: PESCADF unit root test for real estate

. pescadf realestate, lags(4)	
Pesaran's CADF test for realestate	
Cross-sectional average in first period extracted and	extreme t-values truncated
Deterministics chosen: constant	
panel is unbalanced, only standarized Ztbar statistic	can be calculated
Z[t-bar] test, (N,T1-T4) = (4, 126 113 126 126)	
Obs = 471 Augmented by 4 lags (average)	
Z[t-bar] P-value	
-2.581 0.000	

APPENDIX 71: PESCADF unit root test for emerging markets general stock returns

. pescadf compositestock, lags(4)				
Pesaran's CADF test for compositestock				
Cross-sectional average in first period	Extracted	and extreme	t-values	truncated
Deterministics chosen: constant				
t-bar test, N,T = (4,126) Obs =	484			
Augmented by 4 lags (average)				
t-bar cv10 cv5 cv1	Z[t-bar]	P-value		
2.610 -2.210 -2.320 -2.530	-2.893	0.000		

APPENDIX 72: PESCADF unit root test for inflation

pescadf d.inflation, lags(4)				
Pesaran's CADF test for D.inflation				
Cross-sectional average in first period	Extracted	and extreme	t-values	truncated
Deterministics chosen: constant				
t-bar test, N,T = (4,125) Obs =	480			
Augmented by 4 lags (average)				
t-bar cv10 cv5 cv1	Z[t-bar]	P-value		
2.610 -2.210 -2.320 -2.530	-4.629	0.000		

APPENDIX 73: PESCADF unit root test for infrastructure

Pesaran's CADF test for D.infrastructure	
Cross-sectional average in first period extracted and	extreme t-values truncated
Deterministics chosen: constant	
panel is unbalanced, only standarized Ztbar statistic	can be calculated
Z[t-bar] test, (N,T1-T4) = (4, 43 125 106 125)	
Obs = 374 Augmented by 4 lags (average)	
Z[t-bar] P-value	
-3.873 0.000	

APPENDIX 74: PESCADF unit root test for crude oil

escadf crudeoil, lags(4)	
Pesaran's CADF test for crudeoil	
Cross-sectional average in first period extracted and	extreme t-values truncated
Deterministics chosen: constant	
panel is unbalanced, only standarized Ztbar statistic	can be calculated
Z[t-bar] test, (N,T1-T4) = (4, 126 126 126 121)	
Obs = 479 Augmented by 4 lags (average)	
Z[t-bar] P-value	
-5.924 0.000	

APPENDIX 75: Pooled Mean Group (PMG) estimates for model 1

```
. xtpmg d.infrastructure d.inflation d.gdp d.crudeoil, lr(l.infrastructure l.in
> flation l.gdp l.crudeoil) ec(ec) replace pmg full

Iteration 0:   log likelihood =  524.10491
Iteration 1:   log likelihood =   525.1337
Iteration 2:   log likelihood =  525.13378
Iteration 3:   log likelihood =  525.13378

Pooled Mean Group Regression
(Estimate results saved as PMG)

Panel Variable (i): id                           Number of obs       =       394
Time Variable (t): month                         Number of groups    =         4
                                                 Obs per group: min  =        43
                                                                avg  =      98.5
                                                                max  =       125

                                                 Log Likelihood      =  525.1338

------------------------------------------------------------------------------
D.           |
infrastruc~e |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ec           |
   inflation |
         L1. |  -.0099936   .0069557    -1.44   0.151    -.0236265    .0036393
             |
         gdp |
         L1. |   .0012854     .00583     0.22   0.825    -.0101413    .0127121
             |
    crudeoil |
         L1. |   .0799159   .0528343     1.51   0.130    -.0236374    .1834691
-------------+----------------------------------------------------------------
id_1         |
          ec |  -.8327647   .1498709    -5.56   0.000    -1.126506   -.5390231
             |
   inflation |
         D1. |    -.10174   .0548855    -1.85   0.064    -.2093137    .0058337
             |
         gdp |
         D1. |   .0070576   .0244612     0.29   0.773    -.0408855    .0550006
             |
    crudeoil |
         D1. |   .0838369   .1415095     0.59   0.554    -.1935166    .3611904
             |
       _cons |   .0092584   .0151662     0.61   0.542    -.0204668    .0389837
-------------+----------------------------------------------------------------
id_2         |
          ec |   -.939361   .0891387   -10.54   0.000     -1.11407   -.7646523
             |
   inflation |
         D1. |  -.0116217   .0114926    -1.01   0.312    -.0341467    .0109033
             |
         gdp |
         D1. |   .0092711   .0193044     0.48   0.631    -.0285647    .0471069
             |
    crudeoil |
         D1. |   .0214425   .0837901     0.26   0.798     -.142783    .1856681
             |
       _cons |   .0034254   .0136719     0.25   0.802     -.023371    .0302218
-------------+----------------------------------------------------------------
id_3         |
          ec |  -1.026632   .0922697   -11.13   0.000    -1.207477   -.8457862
             |
   inflation |
         D1. |   .0100252   .0073206     1.37   0.171     -.004323    .0243734
             |
         gdp |
         D1. |   .0348581   .0184349     1.89   0.059    -.0012735    .0709898
             |
    crudeoil |
         D1. |  -.0753794   .0728908    -1.03   0.301    -.2182427    .0674838
             |
       _cons |   .0058859   .0121964     0.48   0.629    -.0180187    .0297905
------------------------------------------------------------------------------

id_4         |
          ec |  -.9228809   .0894714   -10.31   0.000    -1.098242   -.7475201
             |
   inflation |
         D1. |   .0082494   .0079472     1.04   0.299    -.0073269    .0238256
             |
         gdp |
         D1. |   -.071746   .0343416    -2.09   0.037    -.1390542   -.0044377
             |
    crudeoil |
         D1. |  -.0019807   .0497624    -0.04   0.968    -.0995132    .0955517
             |
       _cons |   .0084649   .0087123     0.97   0.331     -.008611    .0255408
------------------------------------------------------------------------------
```

APPENDIX 76: PMG estimates for model 2

```
. xtpmg d.realestate d.inflation d.gdp d.crudeoil, lr(l.realestate l.inflation
> l.gdp l.crudeoil) ec(ec) replace pmg full

Iteration 0:   log likelihood =  490.70853
Iteration 1:   log likelihood =   491.1242
Iteration 2:   log likelihood =  491.12421

Pooled Mean Group Regression
(Estimate results saved as PMG)

Panel Variable (i): id                          Number of obs      =       482
Time Variable (t): month                        Number of groups   =         4
                                                Obs per group: min =       112
                                                               avg =     120.5
                                                               max =       125

                                                Log Likelihood     =  491.1242
```

D.realestate	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.0082492	.0104906	-0.79	0.432	-.0288103	.0123119
gdp L1.	.0075373	.0058709	1.28	0.199	-.0039695	.0190441
crudeoil L1.	.0360823	.073177	0.49	0.622	-.1073419	.1795066
id_1						
ec	-.9236079	.0849656	-10.87	0.000	-1.090137	-.7570783
inflation D1.	-.0210472	.028806	-0.73	0.465	-.0775058	.0354114
gdp D1.	.0561949	.0131259	4.28	0.000	.0304685	.0819212
crudeoil D1.	-.0412858	.0902988	-0.46	0.648	-.2182682	.1356966
_cons	.0120543	.0091311	1.32	0.187	-.0058423	.0299509
id_2						
ec	-.917057	.0939576	-9.76	0.000	-1.10121	-.7329035
inflation D1.	-.0215729	.0124802	-1.73	0.084	-.0460337	.0028879
gdp D1.	-.0141657	.0341257	-0.42	0.678	-.0810508	.0527193
crudeoil D1.	.0022142	.0939839	0.02	0.981	-.1819908	.1864192
_cons	-.0079703	.012907	-0.62	0.537	-.0332676	.017327
id_3						
ec	-.9266476	.0881505	-10.51	0.000	-1.099419	-.7538758
inflation D1.	.0107686	.0112956	0.95	0.340	-.0113704	.0329075
gdp D1.	.0337355	.0142296	2.37	0.018	.0058461	.0616249
crudeoil D1.	-.0063176	.1243989	-0.05	0.959	-.250135	.2374998
_cons	.0008141	.0158451	0.05	0.959	-.0302416	.0318698
id_4						
ec	-.8642429	.0896907	-9.64	0.000	-1.040033	-.6884523
inflation D1.	-.008591	.0119441	-0.72	0.472	-.032001	.014819
gdp D1.	-.0101601	.0522802	-0.19	0.846	-.1126274	.0923072
crudeoil D1.	-.0556654	.0734248	-0.76	0.448	-.1995754	.0882446
_cons	.0072629	.0098735	0.74	0.462	-.0120888	.0266146

id_4						
ec	-.8642429	.0896907	-9.64	0.000	-1.040033	-.6884523
inflation D1.	-.008591	.0119441	-0.72	0.472	-.032001	.014819
gdp D1.	-.0101601	.0522802	-0.19	0.846	-.1126274	.0923072
crudeoil D1.	-.0556654	.0734248	-0.76	0.448	-.1995754	.0882446
_cons	.0072629	.0098735	0.74	0.462	-.0120888	.0266146

APPENDIX 77: PMG estimates for model 3

```
. xtpmg d.compositestock d.inflation d.gdp d.crudeoil, lr(l.compositestock l.in
> flation l.gdp l.crudeoil) ec(ec) replace pmg full

Iteration 0:   log likelihood =  706.58428
Iteration 1:   log likelihood =  707.39426
Iteration 2:   log likelihood =  707.39465
Iteration 3:   log likelihood =  707.39465

Pooled Mean Group Regression
(Estimate results saved as PMG)

Panel Variable (i): id                          Number of obs      =       495
Time Variable (t): month                        Number of groups   =         4
                                                Obs per group: min =       120
                                                               avg =     123.8
                                                               max =       125

                                                Log Likelihood     =  707.3947
```

D. composites~k	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.0037962	.0058295	-0.65	0.515	-.0152219	.0076295
gdp L1.	.0057746	.0033123	1.74	0.081	-.0007174	.0122666
crudeoil L1.	.1197929	.0470831	2.54	0.011	.0275117	.212074
id_1						
ec	-.9402528	.0880322	-10.68	0.000	-1.112793	-.7677129
inflation D1.	-.0312255	.0196572	-1.59	0.112	-.069753	.0073019
gdp D1.	.0188612	.0088711	2.13	0.033	.0014741	.0362483
crudeoil D1.	.0766387	.0616706	1.24	0.214	-.0442336	.1975109
_cons	.0068498	.0059401	1.15	0.249	-.0047926	.0184922
id_2						
ec	-.8862415	.0880209	-10.07	0.000	-1.058759	-.7137237
inflation D1.	-.0113802	.0094915	-1.20	0.231	-.0299832	.0072228
gdp D1.	.0185984	.0159161	1.17	0.243	-.0125965	.0497933
crudeoil D1.	.0781169	.0696357	1.12	0.262	-.0583666	.2146005
_cons	-.0052704	.0086517	-0.61	0.542	-.0222273	.0116866
id_3						
ec	-.9985196	.0902155	-11.07	0.000	-1.175339	-.8217005
inflation D1.	.005907	.005275	1.12	0.263	-.0044318	.0162458
gdp D1.	.016564	.0063222	2.62	0.009	.0041728	.0289553
crudeoil D1.	.0272264	.0566878	0.48	0.631	-.0838796	.1383324
_cons	.0043486	.0081819	0.53	0.595	-.0116877	.0203848
id_4						
ec	-.9295348	.0900057	-10.33	0.000	-1.105943	-.753127
inflation D1.	.0009303	.009387	0.10	0.921	-.0174679	.0193285
gdp D1.	-.0148953	.0425675	-0.35	0.726	-.0983262	.0685355
crudeoil D1.	.0158528	.0581498	0.27	0.785	-.0981187	.1298242
_cons	.0067426	.006804	0.99	0.322	-.006593	.0200783

APPENDIX 78: Mean Group (MG) estimates for model 1

```
. xtpmg d.infrastructure d.inflation d.gdp d.crudeoil, lr(l.infrastructure l.in
> flation l.gdp l.crudeoil) ec(ec) replace mg
```

Mean Group Estimation: Error Correction Form
(Estimate results saved as mg)

D.infrastruc~e	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.004511	.0052144	-0.87	0.387	-.014731	.0057089
gdp L1.	.0077157	.0053666	1.44	0.151	-.0028026	.0182339
crudeoil L1.	.1863553	.1206451	1.54	0.122	-.0501048	.4228155
SR						
ec	-.9469066	.0311928	-30.36	0.000	-1.008043	-.8857698
inflation D1.	-.0191372	.0221979	-0.86	0.389	-.0626442	.0243699
gdp D1.	-.0055105	.0230336	-0.24	0.811	-.0506554	.0396345
crudeoil D1.	.0532136	.0830504	0.64	0.522	-.1095623	.2159894
_cons	.0055551	.0029674	1.87	0.061	-.0002608	.011371

APPENDIX 79: MG estimates for model 2

```
. xtpmg d.realestate d.inflation d.gdp d.crudeoil, lr(l.realestate l.inflation
> l.gdp l.crudeoil) ec(ec) replace mg
```

Mean Group Estimation: Error Correction Form
(Estimate results saved as mg)

D.realestate	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.0115886	.0111483	-1.04	0.299	-.0334388	.0102617
gdp L1.	.0138537	.0091149	1.52	0.129	-.0040112	.0317187
crudeoil L1.	.0204301	.0449015	0.45	0.649	-.0675752	.1084354
SR						
ec	-.9354255	.0251693	-37.17	0.000	-.9847564	-.8860945
inflation D1.	-.0116997	.0099445	-1.18	0.239	-.0311906	.0077911
gdp D1.	.0185209	.0183796	1.01	0.314	-.0175024	.0545441
crudeoil D1.	-.0334363	.0218018	-1.53	0.125	-.076167	.0092944
_cons	-.0050724	.0154826	-0.33	0.743	-.0354178	.0252729

APPENDIX 80: MG estimates for model 3

```
. xtpmg d.compositestock d.inflation d.gdp d.crudeoil, lr(l.compositestock l.in
> flation l.gdp l.crudeoil) ec(ec) replace mg
```

Mean Group Estimation: Error Correction Form
(Estimate results saved as mg)

D.composites~k	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.0113536	.0077166	-1.47	0.141	-.0264779	.0037707
gdp L1.	.007113	.005054	1.41	0.159	-.0027927	.0170186
crudeoil L1.	.1199996	.0444648	2.70	0.007	.0328501	.207149
SR						
ec	-.9671478	.0383413	-25.22	0.000	-1.042295	-.8920003
inflation D1.	-.011834	.0103471	-1.14	0.253	-.0321139	.008446
gdp D1.	.0096689	.0083103	1.16	0.245	-.006619	.0259569
crudeoil D1.	.0468047	.03561	1.31	0.189	-.0229897	.116599
_cons	.0022972	.0074325	0.31	0.757	-.0122703	.0168647

APPENDIX 81: Dynamic Fixed Effects (DFE) estimates for model 1

```
. xtpmg d.infrastructure d.inflation d.gdp d.crudeoil, lr(l.infrastructure l.in
> flation l.gdp l.crudeoil) ec(ec) replace dfe
```

Dynamic Fixed Effects Regression: Estimated Error Correction Form
(Estimate results saved as DFE)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.0109789	.008502	-1.29	0.197	-.0276426	.0056848
gdp L1.	-.0004573	.005426	-0.08	0.933	-.0110921	.0101775
crudeoil L1.	.1291223	.0624615	2.07	0.039	.0067	.2515447
SR						
ec	-.9409702	.0508154	-18.52	0.000	-1.040567	-.8413739
inflation D1.	-.0001412	.0064737	-0.02	0.983	-.0128294	.0125471
gdp D1.	.0077249	.0105453	0.73	0.464	-.0129436	.0283934
crudeoil D1.	.0287113	.0479312	0.60	0.549	-.0652321	.1226547
_cons	.0090729	.0089491	1.01	0.311	-.0084671	.0266129

APPENDIX 82: DFE estimated for model 2

```
. xtpmg d.realestate d.inflation d.gdp d.crudeoil, lr(l.realestate l.inflation
> l.gdp l.crudeoil) ec(ec) replace dfe
```

Dynamic Fixed Effects Regression: Estimated Error Correction Form
(Estimate results saved as DFE)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.0018332	.0102498	-0.18	0.858	-.0219224	.018256
gdp L1.	.0116042	.0058854	1.97	0.049	.000069	.0231394
crudeoil L1.	.0457277	.0795367	0.57	0.565	-.1101614	.2016168
SR						
ec	-.9245027	.0457751	-20.20	0.000	-1.01422	-.8347851
inflation D1.	.0028639	.0076732	0.37	0.709	-.0121753	.0179031
gdp D1.	.0403217	.0087982	4.58	0.000	.0230775	.0575659
crudeoil D1.	-.0190301	.0590727	-0.32	0.747	-.1348105	.0967503
_cons	-.0034368	.0091687	-0.37	0.708	-.0214072	.0145336

APPENDIX 83: DFE estimates for model 3

```
. xtpmg d.compositestock d.inflation d.gdp d.crudeoil, lr(l.compositestock l.in
> flation l.gdp l.crudeoil) ec(ec) replace dfe
```

Dynamic Fixed Effects Regression: Estimated Error Correction Form
(Estimate results saved as DFE)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ec						
inflation L1.	-.0043222	.0063702	-0.68	0.497	-.0168075	.0081632
gdp L1.	.0038409	.0033512	1.15	0.252	-.0027274	.0104092
crudeoil L1.	.1372793	.0491697	2.79	0.005	.0409084	.2336502
SR						
ec	-.9301951	.0450094	-20.67	0.000	-1.018412	-.8419782
inflation D1.	-.0000489	.0048062	-0.01	0.992	-.009469	.0093712
gdp D1.	.0145555	.0052408	2.78	0.005	.0042837	.0248273
crudeoil D1.	.0549087	.0366253	1.50	0.134	-.0168757	.126693
_cons	.0056263	.0055445	1.01	0.310	-.0052408	.0164934

APPENDIX 84: ADF unit root test for real estate

Null Hypothesis: REAL_ESTATE has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=26)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-47.87277	0.0001
Test critical values:	1% level	-3.432772	
	5% level	-2.862496	
	10% level	-2.567324	

*MacKinnon (1996) one-sided p-values.

APPENDIX 85: KPSS unit root test for real estate

Null Hypothesis: REAL_ESTATE is stationary
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.160186
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000283
HAC corrected variance (Bartlett kernel)	0.000271

APPENDIX 86: PP unit root test for real estate

Null Hypothesis: REAL_ESTATE has a unit root
Exogenous: Constant
Bandwidth: 13 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-47.83875	0.0001
Test critical values:	1% level	-3.432772	
	5% level	-2.862496	
	10% level	-2.567324	

*MacKinnon (1996) one-sided p-values.

APPENDIX 87: ADF unit root test for emerging market stock returns

Null Hypothesis: STOCK_RETURNS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=26)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-40.94825	0.0000
Test critical values:	1% level	-3.432772	
	5% level	-2.862496	
	10% level	-2.567324	

*MacKinnon (1996) one-sided p-values.

APPENDIX 88: PP unit root test for emerging market stock returns

Null Hypothesis: STOCK_RETURNS has a unit root
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-40.33161	0.0000
Test critical values:	1% level	-3.432772	
	5% level	-2.862496	
	10% level	-2.567324	

*MacKinnon (1996) one-sided p-values.

APPENDIX 89: KPSS unit root test for emerging market stock returns

Null Hypothesis: STOCK_RETURNS is stationary
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.032474
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.931393
HAC corrected variance (Bartlett kernel)	1.125517

APPENDIX 90: ADF unit root test for infrastructure

Null Hypothesis: INFRASTRUCTURE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-42.19244	0.0000
Test critical values:	1% level	-3.432669	
	5% level	-2.862450	
	10% level	-2.567300	

*MacKinnon (1996) one-sided p-values.

APPENDIX 91: PP unit root test for infrastructure

Null Hypothesis: INFRASTRUCTURE has a unit root
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-41.79383	0.0000
Test critical values:	1% level	-3.432669	
	5% level	-2.862450	
	10% level	-2.567300	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.884146
HAC corrected variance (Bartlett kernel)	0.784396

APPENDIX 92: KPSS unit root test for infrastructure

Null Hypothesis: INFRASTRUCTURE is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.103448
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.916201
HAC corrected variance (Bartlett kernel)	1.156396

APPENDIX 93: EGARCH estimation under normal distribution (emerging market stock returns)

Dependent Variable: STOCK_RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/14/20 Time: 11:38
Sample (adjusted): 5 2501
Included observations: 2497 after adjustments
Convergence achieved after 24 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.005099	0.018893	-0.269897	0.7872
AR(1)	-0.420238	4.170005	-0.100776	0.9197
AR(2)	0.428926	0.448665	0.956003	0.3391
AR(3)	-0.198946	1.880504	-0.105794	0.9157
AR(4)	-0.126052	1.424342	-0.088499	0.9295
MA(1)	0.615483	4.170802	0.147569	0.8827
MA(2)	-0.303357	1.211445	-0.250409	0.8023
MA(3)	0.135356	1.633583	0.082858	0.9340
MA(4)	0.099533	1.078375	0.092299	0.9265
		Variance Equation		
C(10)	-0.083638	0.010905	-7.669914	0.0000
C(11)	0.102553	0.013196	7.771215	0.0000
C(12)	-0.088731	0.007866	-11.28024	0.0000
C(13)	0.982855	0.003015	326.0087	0.0000

APPENDIX 94: EGARCH estimation under Student's T distribution (emerging market stock returns)

Dependent Variable: STOCK_RETURNS
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 01/14/20 Time: 11:43
Sample (adjusted): 5 2501
Included observations: 2497 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.008373	0.018219	0.459606	0.6458
AR(1)	-0.354344	0.026830	-13.20716	0.0000
AR(2)	0.468846	0.213423	2.196792	0.0280
AR(3)	-0.151056	0.163687	-0.922835	0.3561
AR(4)	-0.066844	0.103707	-0.644550	0.5192
MA(1)	0.548214	0.016560	33.10503	0.0000
MA(2)	-0.356244	0.214424	-1.661402	0.0966
MA(3)	0.071658	0.200293	0.357767	0.7205
MA(4)	0.029841	0.098666	0.302444	0.7623
		Variance Equation		
C(10)	-0.076263	0.013450	-5.669943	0.0000
C(11)	0.092103	0.016598	5.549104	0.0000
C(12)	-0.090077	0.010269	-8.771811	0.0000
C(13)	0.984374	0.003528	279.0191	0.0000
T-DIST. DOF	10.58057	2.121715	4.986801	0.0000

APPENDIX 95: EGARCH estimation under GED (emerging market stock returns)

Dependent Variable: STOCK_RETURNS
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
Date: 01/14/20 Time: 11:44
Sample (adjusted): 5 2501
Included observations: 2497 after adjustments
Convergence achieved after 27 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.012621	0.018002	0.701091	0.4832
AR(1)	-0.428383	2.509659	-0.170694	0.8645
AR(2)	0.451784	0.334573	1.350331	0.1769
AR(3)	-0.142264	1.115214	-0.127567	0.8985
AR(4)	-0.110119	0.867346	-0.126960	0.8990
MA(1)	0.617569	2.510274	0.246017	0.8057
MA(2)	-0.330654	0.742897	-0.445088	0.6563

MA(3)	0.068783	0.987633	0.069644	0.9445
MA(4)	0.069335	0.664560	0.104332	0.9169
		Variance Equation		
C(10)	-0.081391	0.013644	-5.965355	0.0000
C(11)	0.097952	0.016767	5.841876	0.0000
C(12)	-0.088546	0.009880	-8.962008	0.0000
C(13)	0.983491	0.003720	264.3848	0.0000
GED PARAMETER	1.586165	0.061920	25.61646	0.0000

APPENDIX 96: EGARCH estimation under normal distribution (infrastructure)

Dependent Variable: INFRASTRUCTURE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/11/19 Time: 17:37
Sample (adjusted): 5 2604
Included observations: 2600 after adjustments
Convergence achieved after 35 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.013947	0.018884	0.738549	0.4602
AR(1)	-0.264670	3.908975	-0.067708	0.9460
AR(2)	0.223665	2.398935	0.093235	0.9257
AR(3)	-0.335368	0.334380	-1.002957	0.3159
AR(4)	0.101385	1.118952	0.090608	0.9278
MA(1)	0.451401	3.910505	0.115433	0.9081
MA(2)	-0.136119	3.123312	-0.043582	0.9652
MA(3)	0.274277	0.540601	0.507355	0.6119
MA(4)	-0.087613	1.060296	-0.082630	0.9341
		Variance Equation		
C(10)	-0.099924	0.013489	-7.408098	0.0000
C(11)	0.119999	0.016442	7.298327	0.0000
C(12)	-0.071220	0.008074	-8.821388	0.0000
C(13)	0.976561	0.004098	238.3164	0.0000

APPENDIX 97: EGARCH estimation under Student's T distribution (infrastructure)

Dependent Variable: INFRASTRUCTURE
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 07/11/19 Time: 18:02
Sample (adjusted): 5 2604
Included observations: 2600 after adjustments
Convergence achieved after 35 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.027642	0.017849	1.548676	0.1215
AR(1)	-0.238953	3.456431	-0.069133	0.9449
AR(2)	0.266737	1.447420	0.184284	0.8538
AR(3)	-0.373951	0.715078	-0.522951	0.6010
AR(4)	0.064063	1.185279	0.054049	0.9569
MA(1)	0.416184	3.456861	0.120394	0.9042
MA(2)	-0.185551	2.052535	-0.090401	0.9280
MA(3)	0.304852	0.409926	0.743676	0.4571
MA(4)	-0.055352	1.016421	-0.054458	0.9566
		Variance Equation		
C(10)	-0.079380	0.014804	-5.362042	0.0000
C(11)	0.094726	0.018309	5.173656	0.0000
C(12)	-0.062980	0.009969	-6.317706	0.0000
C(13)	0.983193	0.004474	219.7588	0.0000
T-DIST. DOF	8.940092	1.379994	6.478356	0.0000

APPENDIX 98: EGARCH estimation under GED (infrastructure)

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
Date: 07/11/19 Time: 18:05
Sample (adjusted): 5 2604
Included observations: 2600 after adjustments
Convergence achieved after 24 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.025795	0.017748	1.453388	0.1461
AR(1)	-0.785982	2.949335	-0.266495	0.7899
AR(2)	0.069185	1.012687	0.068318	0.9455
AR(3)	-0.273119	0.923631	-0.295702	0.7675
AR(4)	-0.152496	1.001227	-0.152309	0.8789
MA(1)	0.966626	2.949123	0.327767	0.7431
MA(2)	0.107725	1.524620	0.070657	0.9437
MA(3)	0.260953	0.697866	0.373930	0.7085
MA(4)	0.135510	0.787239	0.172134	0.8633
		Variance Equation		
C(10)	-0.089574	0.016237	-5.516688	0.0000
C(11)	0.106847	0.019967	5.351105	0.0000
C(12)	-0.065452	0.010114	-6.471538	0.0000
C(13)	0.980221	0.005002	195.9559	0.0000
GED PARAMETER	1.518938	0.050743	29.93379	0.0000

APPENDIX 99: EGARCH estimation under GED (real estate)

Dependent Variable: REAL_ESTATE
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
Date: 01/14/20 Time: 12:10
Sample (adjusted): 4 2501
Included observations: 2498 after adjustments
Convergence achieved after 32 iterations
MA Backcast: 1 3
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(8) + C(9)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(10)
*RESID(-1)/@SQRT(GARCH(-1)) + C(11)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000153	0.000297	0.514310	0.6070
AR(1)	-0.155258	0.395028	-0.393031	0.6943
AR(2)	-0.374002	0.284646	-1.313921	0.1889
AR(3)	-0.504760	0.224305	-2.250322	0.0244
MA(1)	0.210025	0.392281	0.535393	0.5924
MA(2)	0.353052	0.281889	1.252449	0.2104

MA(3)	0.507996	0.214468	2.368629	0.0179
Variance Equation				
C(8)	-0.508015	0.116981	-4.342733	0.0000
C(9)	0.169738	0.026807	6.331878	0.0000
C(10)	-0.035486	0.014345	-2.473782	0.0134
C(11)	0.954228	0.012687	75.21202	0.0000
GED PARAMETER	1.452109	0.035762	40.60425	0.0000

APPENDIX 100: EGARCH estimation under Student's T distribution (real estate)

Dependent Variable: REAL_ESTATE
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 01/14/20 Time: 12:10
Sample (adjusted): 4 2501
Included observations: 2498 after adjustments
Convergence achieved after 30 iterations
MA Backcast: 1 3
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(8) + C(9)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(10)
*RESID(-1)/@SQRT(GARCH(-1)) + C(11)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000188	0.000304	0.618395	0.5363
AR(1)	0.129244	0.018053	7.159050	0.0000
AR(2)	-0.740737	0.010493	-70.59385	0.0000
AR(3)	-0.440548	0.017984	-24.49654	0.0000
MA(1)	-0.077994	0.002640	-29.53803	0.0000
MA(2)	0.713245	0.001849	385.7918	0.0000
MA(3)	0.495063	0.002604	190.1171	0.0000
Variance Equation				
C(8)	-0.432311	0.095170	-4.542533	0.0000
C(9)	0.163925	0.023987	6.833820	0.0000
C(10)	-0.040951	0.013460	-3.042396	0.0023
C(11)	0.963049	0.010310	93.41336	0.0000
T-DIST. DOF	8.950035	1.084172	8.255183	0.0000

APPENDIX 101: EGARCH estimation under normal distribution (real estate)

Dependent Variable: REAL_ESTATE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/14/20 Time: 12:11
Sample (adjusted): 4 2501
Included observations: 2498 after adjustments
Convergence achieved after 27 iterations
MA Backcast: 1 3
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(8) + C(9)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(10)
*RESID(-1)/@SQRT(GARCH(-1)) + C(11)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000264	0.000324	0.814572	0.4153
AR(1)	-0.000833	0.019728	-0.042232	0.9663
AR(2)	-0.802317	0.008925	-89.89283	0.0000
AR(3)	-0.433761	0.020016	-21.67048	0.0000
MA(1)	0.056981	0.007184	7.931355	0.0000
MA(2)	0.782956	0.003701	211.5626	0.0000
MA(3)	0.491313	0.006943	70.76475	0.0000
Variance Equation				
C(8)	-0.664572	0.107442	-6.185397	0.0000
C(9)	0.185856	0.022560	8.238472	0.0000
C(10)	-0.029353	0.011586	-2.533591	0.0113
C(11)	0.936741	0.011665	80.30463	0.0000

APPENDIX 102: GJR-GARCH estimation under GED (infrastructure)

Dependent Variable: INFRASTRUCTURE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/11/19 Time: 17:39
Sample (adjusted): 5 2604
Included observations: 2600 after adjustments
Convergence achieved after 5 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.017220	0.019148	0.899284	0.3685
AR(1)	0.178903	0.020139	8.883232	0.0000
AR(2)	0.315055	0.017703	17.79653	0.0000
AR(3)	-0.718476	0.016882	-42.55835	0.0000
AR(4)	0.115317	0.023682	4.869417	0.0000
MA(1)	0.011348	0.000972	11.67432	0.0000
MA(2)	-0.324363	0.010007	-32.41369	0.0000
MA(3)	0.633919	0.009685	65.45426	0.0000
MA(4)	-0.017027	0.009253	-1.840081	0.0658
Variance Equation				

C	0.045711	0.007134	6.407651	0.0000
RESID(-1)^2	0.036168	0.011477	3.151411	0.0016
RESID(-1)^2*(RESID(-1)<0)	0.118787	0.014876	7.985277	0.0000
GARCH(-1)	0.846575	0.015847	53.42215	0.0000

APPENDIX 103: GJR-GARCH estimation under Student's T distribution (infrastructure)

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 07/11/19 Time: 18:00
Sample (adjusted): 5 2604
Included observations: 2600 after adjustments
Failure to improve Likelihood after 10 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.030717	0.017860	1.719876	0.0855
AR(1)	-0.018595	0.019888	-0.934992	0.3498
AR(2)	0.370579	0.057174	6.481606	0.0000
AR(3)	-0.535642	0.020846	-25.69545	0.0000
AR(4)	0.051678	0.051450	1.004428	0.3152
MA(1)	0.197907	0.000538	368.1507	0.0000
MA(2)	-0.338939	0.060004	-5.648647	0.0000
MA(3)	0.444406	0.019664	22.59992	0.0000
MA(4)	-0.004839	0.045883	-0.105472	0.9160
		Variance Equation		
C	0.019985	0.005202	3.841559	0.0001
RESID(-1)^2	0.024320	0.012485	1.948022	0.0514
RESID(-1)^2*(RESID(-1)<0)	0.071460	0.015338	4.659136	0.0000
GARCH(-1)	0.913790	0.014324	63.79509	0.0000
T-DIST. DOF	8.740276	1.364984	6.403208	0.0000

APPENDIX 104: GJR-GARCH estimation under GED (infrastructure)

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
Date: 07/11/19 Time: 18:03
Sample (adjusted): 5 2604
Included observations: 2600 after adjustments
Convergence achieved after 27 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.028591	0.017747	1.610980	0.1072
AR(1)	-0.966556	0.292919	-3.299742	0.0010
AR(2)	-0.240226	0.441042	-0.544679	0.5860
AR(3)	0.106504	0.260863	0.408275	0.6831
AR(4)	-0.321577	0.098296	-3.271532	0.0011
MA(1)	1.146251	0.293527	3.905095	0.0001
MA(2)	0.446599	0.496561	0.899384	0.3684
MA(3)	-0.057192	0.344050	-0.166231	0.8680
MA(4)	0.244590	0.100439	2.435213	0.0149
Variance Equation				
C	0.021632	0.005411	3.997914	0.0001
RESID(-1)^2	0.025088	0.012988	1.931645	0.0534
RESID(-1)^2*(RESID(-1)<0)	0.077405	0.015423	5.018883	0.0000
GARCH(-1)	0.907857	0.015155	59.90522	0.0000
GED PARAMETER	1.508842	0.051541	29.27478	0.0000

APPENDIX 105: GJR-GARCH estimation under GED (emerging market general stock returns)

Dependent Variable: STOCK_RETURNS
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
Date: 01/14/20 Time: 11:45
Sample (adjusted): 5 2501
Included observations: 2497 after adjustments
Convergence achieved after 23 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.020869	0.017759	1.175117	0.2399
AR(1)	-0.214957	2.627672	-0.081805	0.9348
AR(2)	0.465542	0.310891	1.497442	0.1343
AR(3)	-0.254068	1.090793	-0.232921	0.8158
AR(4)	-0.055088	0.951262	-0.057910	0.9538
MA(1)	0.399673	2.627894	0.152089	0.8791
MA(2)	-0.392343	0.750725	-0.522619	0.6012

MA(3)	0.168007	0.969320	0.173325	0.8624
MA(4)	0.031531	0.745618	0.042289	0.9663
Variance Equation				
C	0.014005	0.003344	4.187764	0.0000
RESID(-1)^2	-0.001665	0.009499	-0.175325	0.8608
RESID(-1)^2*(RESID(-1)<0)	0.116099	0.014919	7.781913	0.0000
GARCH(-1)	0.925995	0.010806	85.69284	0.0000
GED PARAMETER	1.571922	0.061610	25.51418	0.0000

APPENDIX 106: GJR-GARCH estimation under Student's T distribution (emerging market general stock returns)

Dependent Variable: STOCK_RETURNS
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 01/14/20 Time: 11:46
Sample (adjusted): 5 2501
Included observations: 2497 after adjustments
Convergence achieved after 20 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.016589	0.017976	0.922799	0.3561
AR(1)	-0.368081	3.284388	-0.112070	0.9108
AR(2)	0.476767	0.308992	1.542976	0.1228
AR(3)	-0.174362	1.487898	-0.117187	0.9067
AR(4)	-0.110268	1.173738	-0.093946	0.9252
MA(1)	0.556586	3.285321	0.169416	0.8655
MA(2)	-0.370632	0.858197	-0.431873	0.6658
MA(3)	0.092514	1.339282	0.069077	0.9449
MA(4)	0.072707	0.892609	0.081454	0.9351
Variance Equation				
C	0.013387	0.003187	4.199967	0.0000
RESID(-1)^2	-0.003785	0.009231	-0.410066	0.6818
RESID(-1)^2*(RESID(-1)<0)	0.115739	0.015427	7.502293	0.0000
GARCH(-1)	0.929472	0.010235	90.80998	0.0000
T-DIST. DOF	10.24121	2.027007	5.052378	0.0000

APPENDIX 107: GJR-GARCH estimation under normal distribution (emerging market general stock returns)

Dependent Variable: STOCK_RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/14/20 Time: 11:46
Sample (adjusted): 5 2501
Included observations: 2497 after adjustments
Convergence achieved after 23 iterations
MA Backcast: 1 4
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006326	0.018694	0.338407	0.7351
AR(1)	-0.469766	2.595368	-0.181002	0.8564
AR(2)	0.457051	0.265074	1.724238	0.0847
AR(3)	-0.179934	1.268728	-0.141822	0.8872
AR(4)	-0.177805	0.946994	-0.187757	0.8511
MA(1)	0.660339	2.595914	0.254376	0.7992
MA(2)	-0.331949	0.605495	-0.548227	0.5835
MA(3)	0.109338	1.176669	0.092922	0.9260
MA(4)	0.142597	0.704704	0.202350	0.8396
		Variance Equation		
C	0.014115	0.002644	5.337643	0.0000
RESID(-1)^2	3.34E-07	0.007468	4.47E-05	1.0000
RESID(-1)^2*(RESID(-1)<0)	0.117526	0.011707	10.03911	0.0000
GARCH(-1)	0.924983	0.008600	107.5543	0.0000

APPENDIX 108: GJR-GARCH estimation under normal distribution (real estate)

Dependent Variable: REAL_ESTATE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/14/20 Time: 12:08
Sample (adjusted): 4 2501
Included observations: 2498 after adjustments
Convergence achieved after 39 iterations
MA Backcast: 1 3
Presample variance: backcast (parameter = 0.7)
GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*RESID(-1)^2*(RESID(-1)<0) +
C(11)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000251	0.000326	0.768687	0.4421
AR(1)	-0.376660	0.542515	-0.694285	0.4875
AR(2)	-0.277200	0.542384	-0.511076	0.6093
AR(3)	-0.392942	0.233607	-1.682068	0.0926
MA(1)	0.440590	0.542124	0.812711	0.4164
MA(2)	0.278782	0.552158	0.504896	0.6136
MA(3)	0.389388	0.247854	1.571036	0.1162

Variance Equation				
C	1.62E-05	2.99E-06	5.409053	0.0000
RESID(-1)^2	0.073391	0.014826	4.949996	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.030354	0.016391	1.851925	0.0640
GARCH(-1)	0.854865	0.020559	41.58202	0.0000

APPENDIX 109: GJR-GARCH estimation under Student's T distribution (real estate)

Dependent Variable: REAL_ESTATE
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 01/14/20 Time: 12:09
Sample (adjusted): 4 2501
Included observations: 2498 after adjustments
Convergence achieved after 37 iterations
MA Backcast: 1 3
Presample variance: backcast (parameter = 0.7)
GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*RESID(-1)^2*(RESID(-1)<0) + C(11)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000244	0.000308	0.794528	0.4269
AR(1)	-1.219037	0.213733	-5.703557	0.0000
AR(2)	-1.312613	0.123859	-10.59762	0.0000
AR(3)	-0.609490	0.203396	-2.996574	0.0027
MA(1)	1.274435	0.203345	6.267342	0.0000
MA(2)	1.363436	0.120053	11.35695	0.0000
MA(3)	0.661076	0.195631	3.379188	0.0007
Variance Equation				
C	1.12E-05	3.01E-06	3.715130	0.0002
RESID(-1)^2	0.067236	0.016558	4.060589	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.048466	0.021493	2.255000	0.0241
GARCH(-1)	0.870539	0.020871	41.70984	0.0000
T-DIST. DOF	9.367646	1.122239	8.347281	0.0000

APPENDIX 110: GJR-GARCH estimation under GED (real estate)

Dependent Variable: REAL_ESTATE
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
Date: 01/14/20 Time: 12:09
Sample (adjusted): 4 2501
Included observations: 2498 after adjustments
Convergence achieved after 37 iterations
MA Backcast: 1 3
Presample variance: backcast (parameter = 0.7)
GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*RESID(-1)^2*(RESID(-1)<0) +
C(11)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000160	0.000301	0.531928	0.5948
AR(1)	-1.345902	0.106288	-12.66277	0.0000
AR(2)	-1.143170	0.136159	-8.395843	0.0000
AR(3)	-0.785266	0.087044	-9.021456	0.0000
MA(1)	1.394018	0.105550	13.20718	0.0000
MA(2)	1.199655	0.137817	8.704700	0.0000
MA(3)	0.800644	0.083083	9.636731	0.0000
		Variance Equation		
C	1.28E-05	3.59E-06	3.568185	0.0004
RESID(-1)^2	0.068024	0.017978	3.783624	0.0002
RESID(-1)^2*(RESID(-1)<0)	0.038294	0.022041	1.737402	0.0823
GARCH(-1)	0.868879	0.023949	36.28006	0.0000
GED PARAMETER	1.457699	0.035848	40.66359	0.0000

APPENDIX 111: GJR-GARCH loss functions estimation under normal distribution (infrastructure)

Forecast: INFRASTRUCTUREF
Actual: INFRASTRUCTURE
Forecast sample: 1 2605
Adjusted sample: 5 2605
Included observations: 2600

Root Mean Squared Error	0.956991
Mean Absolute Error	0.701414
Mean Absolute Percentage Error	116.5164
Theil Inequality Coefficient	0.960419
Bias Proportion	0.000002
Variance Proportion	0.929290
Covariance Proportion	0.070708

APPENDIX 112: GJR-GARCH loss functions estimation under Student's T distribution (infrastructure)

Forecast: INFRASTRUCTUREF
Actual: INFRASTRUCTURE
Forecast sample: 1 2605
Adjusted sample: 5 2605
Included observations: 2600

Root Mean Squared Error	0.957050
Mean Absolute Error	0.701146
Mean Absolute Percentage Error	128.3529
Theil Inequality Coefficient	0.953550
Bias Proportion	0.000159
Variance Proportion	0.930242
Covariance Proportion	0.069598

APPENDIX 113: GJR-GARCH loss functions estimation GED (infrastructure)

Forecast: INFRASTRUCTUREF
Actual: INFRASTRUCTURE
Forecast sample: 1 2605
Adjusted sample: 5 2605
Included observations: 2600

Root Mean Squared Error	0.956474
Mean Absolute Error	0.700622
Mean Absolute Percentage Error	123.4314
Theil Inequality Coefficient	0.951905
Bias Proportion	0.000108
Variance Proportion	0.924827
Covariance Proportion	0.075065

APPENDIX 114: EGARCH loss functions estimation under normal distribution (infrastructure)

Forecast: INFRASTRUCTUREF
Actual: INFRASTRUCTURE
Forecast sample: 1 2605
Adjusted sample: 5 2605
Included observations: 2600

Root Mean Squared Error	0.957256
Mean Absolute Error	0.702034
Mean Absolute Percentage Error	110.7273
Theil Inequality Coefficient	0.970782
Bias Proportion	0.000024
Variance Proportion	0.949010
Covariance Proportion	0.050966

APPENDIX 115: EGARCH loss functions estimation under Student's T distribution (infrastructure)

Forecast: INFRASTRUCTUREF
Actual: INFRASTRUCTURE
Forecast sample: 1 2605
Adjusted sample: 5 2605
Included observations: 2600

Root Mean Squared Error	0.957231
Mean Absolute Error	0.701522

Mean Absolute Percentage Error	122.9204
Theil Inequality Coefficient	0.960401
Bias Proportion	0.000088
Variance Proportion	0.943405
Covariance Proportion	0.056507

APPENDIX 116: EGARCH loss functions estimation under GED (infrastructure)

Forecast: INFRASTRUCTUREF
Actual: INFRASTRUCTURE
Forecast sample: 1 2605
Adjusted sample: 5 2605
Included observations: 2600

Root Mean Squared Error	0.957139
Mean Absolute Error	0.701488
Mean Absolute Percentage Error	121.5730
Theil Inequality Coefficient	0.961164
Bias Proportion	0.000055
Variance Proportion	0.942432
Covariance Proportion	0.057513

APPENDIX 117: GJR-GARCH loss functions estimation under Student's T distribution (real estate)

Forecast: REAL_ESTATF
Actual: REAL_ESTATE
Forecast sample: 1 2502
Adjusted sample: 4 2502
Included observations: 2498

Root Mean Squared Error	0.016796
Mean Absolute Error	0.012605
Mean Absolute Percentage Error	100.8436
Theil Inequality Coefficient	0.941294
Bias Proportion	0.000047
Variance Proportion	0.890304
Covariance Proportion	0.109649

APPENDIX 118: GJR-GARCH loss functions estimation under normal distribution (real estate)

Forecast: REAL_ESTATF
Actual: REAL_ESTATE
Forecast sample: 1 2502
Adjusted sample: 4 2502
Included observations: 2498

Root Mean Squared Error	0.016827
Mean Absolute Error	0.012615
Mean Absolute Percentage Error	99.21492
Theil Inequality Coefficient	0.982300
Bias Proportion	0.000045
Variance Proportion	0.980601
Covariance Proportion	0.019354

APPENDIX 119: GJR-GARCH loss functions estimation under GED (real estate)

Forecast: REAL_ESTATF
Actual: REAL_ESTATE
Forecast sample: 1 2502
Adjusted sample: 4 2502
Included observations: 2498

Root Mean Squared Error	0.016803
Mean Absolute Error	0.012600
Mean Absolute Percentage Error	100.8388
Theil Inequality Coefficient	0.954064
Bias Proportion	0.000142
Variance Proportion	0.914096
Covariance Proportion	0.085761

APPENDIX 120: GJR-GARCH loss functions estimation under normal distribution (emerging markets stock returns)

Forecast: STOCK_RETUF
Actual: STOCK_RETURNS
Forecast sample: 1 2502
Adjusted sample: 5 2502
Included observations: 2497

Root Mean Squared Error	0.965130
Mean Absolute Error	0.709564
Mean Absolute Percentage Error	101.0688
Theil Inequality Coefficient	0.990256
Bias Proportion	0.000406
Variance Proportion	0.983170
Covariance Proportion	0.016424

APPENDIX 121: GJR-GARCH loss functions estimation under Student's T distribution (emerging markets stock returns)

Forecast: STOCK_RETUF
Actual: STOCK_RETURNS
Forecast sample: 1 2502
Adjusted sample: 5 2502
Included observations: 2497

Root Mean Squared Error	0.964952
Mean Absolute Error	0.708881
Mean Absolute Percentage Error	102.0742
Theil Inequality Coefficient	0.989304
Bias Proportion	0.000036
Variance Proportion	0.987152
Covariance Proportion	0.012811

APPENDIX 122: GJR-GARCH loss functions estimation under GED (emerging markets stock returns)

Forecast: STOCK_RETUF
Actual: STOCK_RETURNS
Forecast sample: 1 2502
Adjusted sample: 5 2502
Included observations: 2497

Root Mean Squared Error	0.964934
Mean Absolute Error	0.708710
Mean Absolute Percentage Error	103.4224
Theil Inequality Coefficient	0.985261
Bias Proportion	0.000002
Variance Proportion	0.986027
Covariance Proportion	0.013971

APPENDIX 123: EGARCH loss functions estimation under normal distribution (emerging markets stock returns)

Forecast: STOCK_RETUF
Actual: STOCK_RETURNS
Forecast sample: 1 2502
Adjusted sample: 5 2502
Included observations: 2497

Root Mean Squared Error	0.965130
Mean Absolute Error	0.709564
Mean Absolute Percentage Error	101.0688
Theil Inequality Coefficient	0.990256
Bias Proportion	0.000406
Variance Proportion	0.983170
Covariance Proportion	0.016424

APPENDIX 124: EGARCH loss functions estimation under Student's T distribution (emerging markets stock returns)

Forecast: STOCK_RETUF
Actual: STOCK_RETURNS
Forecast sample: 1 2502
Adjusted sample: 5 2502
Included observations: 2497

Root Mean Squared Error	0.964952
Mean Absolute Error	0.708881
Mean Absolute Percentage Error	102.0742
Theil Inequality Coefficient	0.989304
Bias Proportion	0.000036
Variance Proportion	0.987152
Covariance Proportion	0.012811

APPENDIX 125: EGARCH loss functions estimation under GED (emerging markets stock returns)

Forecast: STOCK_RETUF
Actual: STOCK_RETURNS
Forecast sample: 1 2502
Adjusted sample: 5 2502
Included observations: 2497

Root Mean Squared Error	0.964934
Mean Absolute Error	0.708710
Mean Absolute Percentage Error	103.4224
Theil Inequality Coefficient	0.985261
Bias Proportion	0.000002
Variance Proportion	0.986027

Covariance Proportion	0.013971

APPENDIX 126: EGARCH loss functions estimation under normal distribution (real estate)

Forecast: REAL_ESTATF
Actual: REAL_ESTATE
Forecast sample: 1 2502
Adjusted sample: 4 2502
Included observations: 2498

Root Mean Squared Error	0.016802
Mean Absolute Error	0.012610
Mean Absolute Percentage Error	104.2089
Theil Inequality Coefficient	0.935141
Bias Proportion	0.000029
Variance Proportion	0.876076
Covariance Proportion	0.123895

APPENDIX 127: EGARCH loss functions estimation under Student's T distribution (real estate)

Forecast: REAL_ESTATF
Actual: REAL_ESTATE
Forecast sample: 1 2502
Adjusted sample: 4 2502
Included observations: 2498

Root Mean Squared Error	0.016781
Mean Absolute Error	0.012609
Mean Absolute Percentage Error	107.5762
Theil Inequality Coefficient	0.929748
Bias Proportion	0.000097
Variance Proportion	0.867198
Covariance Proportion	0.132705

APPENDIX 128: EGARCH loss functions estimation under GED (real estate)

Forecast: REAL_ESTATF
Actual: REAL_ESTATE
Forecast sample: 1 2502
Adjusted sample: 4 2502
Included observations: 2498

Root Mean Squared Error	0.016826
Mean Absolute Error	0.012612
Mean Absolute Percentage Error	98.84476
Theil Inequality Coefficient	0.981891
Bias Proportion	0.000157
Variance Proportion	0.968989
Covariance Proportion	0.030854