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Wavelet analysis of Stock Market trends: Investigating behavioural patterns in the Johannesburg and London Stock Markets

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DECLARATION

I Ronald Mwenye declare that this research report entitled 'Wavelet analysis of Stock Market trends: Investigating behavioural patterns in the Johannesburg and London Stock Markets' is my own unaided work. I have acknowledged, attributed, and referenced all ideas sourced elsewhere. I am hereby submitting it in partial fulfilment of the requirements of the degree of Master of Business Administration at the University of the Witwatersrand, Johannesburg. I have not submitted this report before for any other degree or examination to any other institution.

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Signed at Johannesburg on 30th February 2020

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ABSTRACT

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This research explores a view that considers price index movements as a reflection of the aggregate rational and sentiment psychological elements of market agents. This perspective asserts that both psychological elements of agent rational and sentiment influence choices that drive price movements in stock markets. To investigate this behavioural link between markets and market agents, the research caries out a time series analysis of Johannesburg and London stock market trends (JSE and FSTE indexes). In examining this link using index price information, the research considers its implications on the conceptualisation of market efficiency by interrogating the very meaning of information.

The research employs a Morlet continuous wavelet transform as a special form of multiresolution analysis for resolving market price signals into information patterns. The research attempts to interpret these information patterns pragmatically in terms of market agents' beliefs about the market through a hypothesis that maps price information to liquidity and agent psychology. The study verifies the plausibility of the research hypothesis by using cross-wavelet analysis to correlate index movements and volatility.

Research results appear to confirm that price index patterns represent agents' belief in the market as an aggregate of their rational and sentiment. Wavelet analysis of the FTSE 100 index demonstrates how changes in market belief or mind-set in 2008 (the global financial crisis) and 2012 (Greece debt crisis) closely relate to its volatility measure, the VIX.

The research concludes that information transparency might not be adequate to qualify market efficiency. Beyond informational transparency is a subjective element of truth that brings market beliefs forth. Studying these beliefs through market rational and sentiment patterns might be key to understanding the market landscape of the future and understanding market horizons to enable better risk-returns forecasting.

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1 INTRODUCTION TO THE RESEARCH

This research conducts a time series analysis of stock market index trends from a behavioural perspective to gain insights on issues around stock market efficiency and market stability, issues that affect investment returns. Principal to market efficiency (Malkiel & Fama, 1970) is a proposition that prices of stocks (Skočir & Lončarski, 2018) reflect all known information about stocks (Dimson & Mussavian, 1998), the availability of this information being positively associated with market volatility or dispersion of returns (Vlastakis & Markellos, 2012). This suggests that transparency of information around a stock drives expected behaviour of its price, with price anomalies indicative of knowledge gaps (Schwert, 2003). Here, information refers to 'knowledge about current or past prices, quotes, or volumes, the sources of order flow, and the identities and motivations of market participants', while transparency is "the ability of market participants to observe the information in the trading process" (Madhavan, 1996 citing O'Hara,1995 p.255). Information and its transparency property are boundless concepts however, with some indication that transparency to market fundamentals alone might not be the only factor around improving the informational efficiency of markets (Banerjee, Davis, & Gondhi, 2018). To this problem, modern finance and economics proposes a behavioural approach to market analysis in shedding more light to efficiency and volatility (Costa, Carvalho, & Moreira, 2019; Sharma & Kumar, 2019).

By definition, a time series is 'an ordered sequence of events or observations having a time component' (Singh, Dutta, & Chakrabarti, 2018, p. 9). Stock market index trends or market signals represent an example of such a time series. Time series analysis of market data enables a systematic understanding of market characteristics (Kılıç & Uğur, 2018; Lavelle, 2019) in relation to the environmental or market context (Jun, Ahn, Kim, & Kim, 2019; Mariani, Bhuiyan, Tweneboah, Beccar-Varela, & Florescu, 2020; Stratimirović, Sarvan, Miljković, & Blesić, 2018). Understanding market signals helps corporates and investors to better adapt to business environments (Engle, Ghysels, & Sohn, 2013; Ho, 2017; Ho & Odhiambo, 2018). This is because by embedding political, ecological, technological, socio-economic and regulatory factors into stock trends, stock markets offer a unique window to the environment around business operations. Thus, analysing market characteristics helps in increasing the understanding of global and local pressures acting on business (Muchaonyerwa & Choga, 2015).

Analysing the time series of stock market trends begins with learning the meaning of information in a general sense and as a critical input to decision making (R. A. Howard, 1966). To this end, important aspects of information, its utility and communication are useful to consider. This includes investigating other known and interesting phenomenon about information, such as information avoidance (Golman, Hagmann, & Loewenstein, 2017). The rational and sentiment elements of information produced by stock market trends and the corresponding market agent interfacing (rational and sentiment) logic that drives stock market behaviour (Antoniou, Doukas, & Subrahmanyam, 2016; DeVault, Sias, & Starks, 2019) is today increasingly central to understanding information. Studying information in relation to stock market trends in this manner reveals interesting ideas that help guide the search for insights from this understanding. It appears that information has value, and its value is desirable for some reasons related to rational and sentimental elements of decision-making around choices on gains and loss. This interaction of rational and sentiment logic in information driven choices is the basis of this research enquiry. In projecting information as a driver of choice in decision-making, an analysis method based on the wave theory is proposed and applied in deconstructing market trends to reveal obscure elements in market information, departing from a classical time view analysis. Comparing the output of this analysis approach to insights from leading market or economic indicators, can help validate this method and the plausibility of its interpretations.

By looking into trends from the Johannesburg Stock Exchange (JSE) and London Stock Exchange (LSE), the research attempts to find reasons for differences between emerging and developed markets. In this, the study looks into the possibility that agents behavioural characteristics are the foundations of market efficiency by claiming that while rational and sentiment are universal elements of human behaviour their composition varies within markets and market places. This assertion shifts the emphasis from information transparency to information interpretation as a driver of market efficiency and stability. However, because information interpretation is a broad idea, this study only focuses on meanings in patterns of variation in ordinary looking data sets that form multi-dimensional structures of information. Comparing the London Stock Exchange (LSE) as a developed market to an emerging market in the form of the Johannesburg Stock Exchange (JSE) provides scenarios that enable an assessment of broad linkages between market outcomes and localities (Roll, 1992).

1.1 Context of and background to the study

It is difficult to dispute the importance of data and information to business operations today (Côrte-Real, Oliveira, & Ruivo, 2017), especially given ongoing efforts to understand the intrinsic meaning of data, information, knowledge, and intelligence (Wang, 2015). Within a business, structured information connects different business functions in the production of value that in turn generates profit in markets. This role of structured information in business makes it essential in the analysis of business fundamentals. Intuitively, such information must be accurate, concise, reliable, available and verifiable amongst other criteria in order to support good decision making around business and investment. External to the business, information sources produce and disseminate unstructured information about the environment. As a dense condensation of causal forms, such information appears random and at times chaotic. Technical analysis methods attempt to discern or isolate relevant variables in such information streams and interpret their risk or opportunity implications to business, the qualification and quantification of such risks or opportunities being in themselves opportunities for further clarity about events taking place in the macro environment.

Understanding meanings embedded in structured and unstructured information is undoubtedly useful. It enables corporates and investors to both judge and perceive market risks and opportunities around their strategies, allowing them ultimately to take appropriate actions through decision-making (Lindblom, Mavruk, & Sjögren, 2017; Pawar, Jawale, & Kyatanavar, 2016). Primarily market indexes have a purpose of providing investors with a clear understanding of market returns (Feeney & Hester, 1964), but additionally they also contain factors internal and external to business that are drivers to the same indexes (Hsing, 2011). As a centralised information source, the index concept is important and cost effective in disseminating market information. However, its information condensation nature may conceal meanings relevant to different market participants. Unlocking this power of information to drive efficiency not only requires a general interrogation of meaning in information but applying context to derive context specific meaning as well. Behavioural analysis of information as an integration of technical and fundamental analysis in a business context can provide this platform. Around this, time series analysis provides a useful approach to isolating the drivers of trends as part of understanding forces affecting business or driving markets.

1.2 Research conceptualisation

Spectral analysis of financial market signals is a common type of time series analysis that uses the Fourier method (Jun et al., 2019). However, a simple spectral analysis of financial market signals is insufficient for developing a time-sensitive two-dimensional frame needed to reveal opportunities for behavioural insights in markets. A key opportunity in this case is linking the rational and sentiment composition of market participants or agents to stock market price movements. This opportunity draws on contemporary and developing notions around investor psychology (Kapoor & Prosad, 2017; Wärneryd, 2001), and the challenge of the research is using mathematical frameworks to understand this link (Aguiar-Conraria & Soares, 2014). Towards this, the research proposes a wave theory based instrument for examining stock market trends in the search for a connection between human or market agent behaviour to market characteristics (Dhaoui, Bourouis, & Boyacioglu, 2013).

The research problem statement

The motivation for this research is combining rational and sentiment into a single element for understanding market price movements. Around this idea, the research problem statement is 'analysis of market agents' behavioural patterns in market index trends using information and liquidity as proxies of rational and sentiment. The research question centres on stock index trends since they offer some representation of markets (Roll, 1992). In this, market indices aggregate agent driven market processes into a time dependent price variable. This price variable reflects continuously changing pressures on stock prices due to actions involved in the buying and selling of stock in the given market. Pressures driving these market processes appear to be chaotic at times but have an underlying order, an order motivated by the market participants' desire to make gains and avoid losses in the market (Benoit, Colliard, Hurlin, & Pérignon, 2017, p. 2). Global and contextual macro-economic rational factors acting on stock markets are being isolated along these lines (Ho, 2017). These factors include exchange rates as market interfaces, structures of industry within markets and index compositions in markets (Hsing, 2011; Roll, 1992), as well as market volume, inflation and interest rates (Ndlovu & Alagidede, 2018). With similar intentions, studies today are shifting to sentiment-induced reasons in market actions (Chau, Deesomsak, & Koutmos, 2016).

The attempt to link information and liquidity as proxies of rational and sentiment focuses on plausibility by looking into possibilities of direct associations between market efficiency and volatility with the psychology of humans as visible participants in free markets. In a practical sense, this problem statement defines an attempt to identify and interpret differences between markets such as the Johannesburg Stock Exchange (JSE) and the London Stock Exchange (LSE) using behavioural signatures within their stock market trends. Stock price trends as outcomes of stock trading form a common aspect of all stock markets, where efficiency defines aspects of determining trading prices and volatility indicates effects of the unknown in this. Using this portrayal of efficiency and volatility the research contends that wavelet analysis can reveal elements of broad market signatures that can present general market characteristics. Intuitively, market forces drive stock market price trends upwards or downwards. The nature of these forces and the best way to understand them becomes a basis for argument.

In line with the preceding, the research hypothesis proposes that wavelet analysis resolves market price signals to fundamental forces whose patterns reveals the behaviour of market agents or market participants. This suggests that collective pressures market participants apply on price is visible through the scale and periodicity of market patterns. Further, this scale and periodicity should correlate with other market indicators like the volatility, consumer sentiment, investor sentiment and other macroeconomic variables in contact with market agents. Thus, the general validity of assumptions made here must be verifiable using such established indicators. The role of the JSE and LSE stock market in this is providing specific contexts for analysing price signals to assess this conceptual connection between wave theory, market energy and a rational-sentiment behavioural construct. In this framing, the rational-sentiment construct forms a basic unit of dynamism and momentum that influences markets and their indices. The following is a formulation of the research thesis supporting this research hypothesis and problem definition:

- Rational and sentiment as critical elements of information have a basic logical relationship that enhances meaning to information.
- Human behaviour as a source and recipient of rational and sentiment is embedded in all facets of market activities.
- Understanding communication of rational and sentiment can help understand market efficiency and volatility.

The research purpose statement

The purpose of this research is to look into information and exploring dimensions of information in ordinary data. Looking into what stock market information actually conveys about markets from price movements and identifying potential gaps of information is a specific case of this. A deeper understanding of information can contribute to a better understanding of "informational efficiency of financial markets" (Dimson & Mussavian, 1998, p. 91), with particular benefits to emerging markets (Gyamfi, Kyei, & Gill, 2017). Motivating this purpose is a simple idea that increased clarity on market risks and opportunities when confronted with questions of resource allocation should definitely improve the quality of decisions made by both corporates and investors, creating more 'allocative or operational' efficient markets (Gyamfi et al., 2017, p. 70). This is an ideal of good resource allocation in sustainable and responsible investing (Busch, Bauer, & Orlitzky, 2016). To achieve this purpose, the study aims to apply a wavelet transform based time-series analysis method to stock market trends on the JSE and LSE. The goal of this approach is to search for systemic behaviour embedded in the JSE and LSE market contexts.

Two broadly encompassing objectives towards achieving this are as follows:

- To formulate a theoretical structure conceptualizing rational and sentiment,
- To apply this structure in a time series analysis of real stock market data.

The JSE and LSE global indices as well as selected securities in telecommunication, retail, banking and mining industries of South Africa form sample spaces for this analysis. By applying theory to practical situations, the analysis may help extend ideas around the efficient market hypothesis to accommodate diversity in market contexts. Markets surely have a unique and measurable character, making market efficiency a continuous rather than the fragmented construct presented by the market efficiency hypothesis. The wavelet transform used in this study is a generic tool for exploring price-time series data in a price-time-frequency domain, which creates a basis of connecting the research thesis to the research problem. In resolving the research enquiry on this basis, the approach to research design leans towards an interpretive line of enquiry where circumstances around the existing market efficiency hypothesis and its possible development form key considerations.

The research questions

The following questions give the research enquiry guidance on what needs attention or resolution in establishing the meaning sort from this research enquiry. Important questions asked are around data and information, nature of financial markets as systems, stability and efficiency in that context, how human behaviour comes into this, tools that can help provide a unifying explanation and ways of validating this thinking.

1. What is data and information in the context of stock markets and its connection to the market efficiency hypothesis?
2. What is a stock market as a system (looking at index construction and environment determinants of index trends and with focus on the JSE and LSE)?
3. How can rational and sentiment help in explaining stock market behaviour?
4. How can wavelet analysis reveal useful information describing structures of stock markets and how can this explain JSE and LSE stock trends?
5. How can evaluating the correlation of derived transformation elements with established market indicators validate this concept of market structural analysis?

1.3 Delimitations and assumptions of the research study

Lightness in academic rigor in validating the thesis of research might limit generalizations from this study. The study attempts to balance conceptualisation and practical reasoning by combining in varying margins elements of deductive and inductive methods in conducting the research. This approach enables an opportunity to verify the validity of thoughts around the research subject at the expense of generalizations. It is a preparation for rigorous future studies towards theory formulation around presented ideas. Thus, this research, given its business context, looks at the research problem from a business perspective, rather than from a purely mathematical and signal analysis point of view. This implies using theory not for its sake but for generating insights useful in business related scenarios. Making reasonable assumptions enables the adoption of theoretical and empirical findings into analysis models that are applicable to market trend analysis from the business point of view.

1.4 Significance of the research study

Classical technical analysis focuses on compound drivers of market indices. This research focuses on methods around elementary drivers, i.e. behaviour of market participants and their cognitive and psychological elements by extension. Corporates and investors can use this in developing more custom economic and market indicators for monitoring various aspects of market activities. The approach presented in this study is also applicable in the analysis of specialised economic or market indicators such as the consumer sentiment, investor sentiment, market volumes and inflation amongst others.

1.5 Preface to the research report

This report has six chapters. Following this introductory chapter, Chapter 2 provides a literature review covering the problem, the past studies, the explanatory framework and the conceptual framework. Chapter 3 discusses the research strategy, design, procedures, reliability and validity measures as well as limitations. Chapter 4 and Chapter 5 present and discuss research findings respectively, while Chapter 6 summarises and defers the research.

2 LITERATURE REVIEW

Literature review attends to the research objective tasked with formulating a theoretical structure for relating rational and sentiment to information and liquidity. With the JSE and LSE in mind, undertaking this part of the research problem begins with examining stock markets focusing on aspects of their nature, operations, importance, economic locality and their synchronisation to the socio-economic and political environment. More critical to this study is an examination of interfaces between stock markets and market agents who participate in various market activities. Concerning this relationship, the study focuses on the information produced by markets and the meaning of this information in reflecting the collective nature of market agents. In this sense literature review broadly explores themes around stock exchange investment (Bodie, Kane, & Marcus, 2019; Rutterford & Davison, 2007) and (financial) information (Libby, Libby, & Hodge, 2017) relevant to the psychology of decision making (Hastie & Dawes, 2010; Hensher, Rose, & Greene, 2005). The aspiration for using cases of stock market index analysis within broad economic contexts (Janse van Rensburg, McConnel, & Brue, 2015) is to enhance a critical connection between markets and corporate strategic thinking (Johnson, Whittington, Scholes, Angwin, & Regner, 2016), with market behavioural insights as intelligence. This framing locates the research problem in business, reveals knowledge gaps and identifies knowledge structures to fill the gaps.

In placing the research problem in literature, literature review endeavours to present a clear position of the research hypothesis by developing its key elements in the manner below. Interpreted in a single form, this assesses aspects of the propagation of rational and sentiment between market participants and markets, and looks for ways of finding patterns identifying behavioural traits of market participants from stock indices.

- Examining market participants behaviour around market trading activities to understand rational and sentiment in choice and decision-making
- Understanding information as a medium for propagating rational and sentiment into all facets of market activities through choice selection and decision making
- Examining stock markets as information sources to understand effects of rational and sentiment within market information on market efficiency and volatility

Developing the research hypothesis in the manner outlined above enables the conceptualisation of the market structure as a linear time invariant system producing non-stationary signals, with the behavioural properties of such a system analysed using signal transformation analysis (Howell, 2016). This is a high level abstraction that attempts to depict market interactions as resembling wave packets (Serway & Jewett, 2018) that propagate in the market driven by rational-sentiment psychological energy (Nofsinger, 2017). Towards this, the focus is using simple and well-understood concepts to formulate a basis for supporting the research hypothesis claiming multiresolution analysis of stock trends as a fundamental decomposition of drivers or forces acting on stock trends. This is an intuitive suggestion that real and aggregate drivers of markets are the fundamental psychological tendencies of market participants; forces acting on the stock market as a system ultimately emanate from stock market participants (i.e. market agents). The research hypothesis impels this exploration of knowledge gaps around understanding stock market psychology along rational-sentiment planes driving the broad characteristics of information and liquidity in given markets, with intentions of looking at how that ultimately interprets to risk and returns of market systems. The following questions guide this exploration in developing a clear position of the research within the context of relevant literature:

- What is a stock market as a system (looking at index construction and environment determinants of index trends, with focus on the JSE and LSE)?
- How can rational and sentiment help in explaining stock market behaviour?
- What is data and information in the context of stock markets and its connection to the market efficiency hypothesis?
- How can wavelet analysis reveal useful information describing psychological structures of stock markets and how can this explain JSE and LSE stock trends?
- How can evaluating the correlation of derived transformation elements with established market indicators validate this concept of market structural analysis?

Supported by these questions, this section proceeds to conceptualize and frame the research hypothesis with a desire of applying it in interpreting wavelet analysis of stock market trends. Literature review focuses on general theoretical considerations sufficient for supporting an interpretive line of enquiry as discussed further in sections examining the philosophical paradigm of the research.

2.1 Research problem analysis

Investigating a behavioural link between markets and market agents requires developing a clear view of the market concept and the role of market agents in it. While the approach to discussing this follows a broad angle, reference to the JSE (Johannesburg Stock Exchange) and LSE (London Stock Exchange) provides specific market contexts. These market contexts, in the form of an emerging market context and developed market context respectively provide data for testing ideas developed around the research problem.

The market concept

To begin with, the concept of a stock market is not only central in this enquiry but is it "one of the most vital components of a free market economy" (Rakhal, 2018). Stock markets are a special type of capital markets where buyers and sellers 'freely' trade in already listed financial assets (Saini, 2018). "The primary role of the capital market is allocation of ownership of the economy's capital stock" (Malkiel & Fama, 1970). Investors and corporates are key participants in this, and in their individual capacity or through intermediaries they supply and demand capital involved in stock market trading (Bodie et al., 2019, p. 11). For investors, stock markets offer opportunities of optimizing risks and returns of investment. Diversifying or spreading investment in the market enables construction of risk-return portfolios matching investors' needs. Meanwhile, corporates requiring capital mobilisation for various business operations compete in the market for available liquid capital by offering, in the case of stock markets, equity with attractive return and risk. The price equilibrium achieved in these interactions forms the basis of allocative efficiency. In part, stock markets sustain this equilibrium through a compromise on long-term capital allowing investors to liquidate their investments by reselling their stocks on the same market. Immediately the role of information in the operational efficiency of markets becomes clear. Fundamental to this is the fact that 'stock prices reflect investor's collective assessment of a corporation's current performance and future prospects' (Bodie et al., 2019, p. 6). However, while investors are mostly interested on rates of return, 'most quoted [stock] indices are price indices, and not indices of rate of return" (Feeney & Hester, 1964, p. 2), making asset prices and their discovery a key interface in finance and economics of investment.

Complexities of understanding variables that determine stock prices extend to complexities in relationships of environmental variables and market variables (Barakat, Elgazzar, & Hanafy, 2016, p. 195 citing Ozbay, 2009). As testimony to this complexity, 'theoretical and empirical literature presents diverse [and localised] views on the relationship between each (macroeconomic) determinants and stock markets" (Ho, 2017). For example, Roll (1992) asserts that the relationship of the stock market to macro environment is in a global sense generally dependent on index construction, industry diversification and the effect of currency conversions in producing common currency returns. A study by Murthy, Anthony, and Vighnesvaran (2016) on the other hand reveals that in the case of the Kuala Lumpur Composite Index, 'interest rate, exchange rate, money supply and oil price' are the critical macroeconomic determinants. Further complicating this image are dependencies between international stock indices (Junior, Mullokandov, & Kenett, 2015). Such evidence suggests that in looking for a consistent framework for the character and structure of a stock market, the market context is key in stock market analysis (Suciu, 2013). This represents an interrogation of diversity in the context of equity markets. From this approach, it would seem intuitive that different stock markets are unique in character and structure. The validity of this offers possible reasons for difficulties in comparing indices from different markets, particularly when looking at market volatility as Roll (1992, pp. 10-14) articulates.

In structure, a stock market's price index is classically presented as a weighted average of commonly held stocks (Feeney & Hester, 1964). A similar view of value weighting in portfolio diversification still holds today, where the stock market index is the most diversified portfolio in the market. The basic principle in this is that a portfolio chosen from such an index is a sub-set of the index portfolio, and thus 'the rate of return of that portfolio then replicates the rate of return of the index' (Bodie et al., 2019, pp. 133, 135). "[This way, the use of indices] helps in representing the entire stock market and [forecasting] the market's movement over time" (Sengupta & Chaudhury, 2018). Using an index to represent an entire market brings forward the same classic questions around efficiency of markets and asset pricing (Firth, 1975), asset pricing and market transparency (Madhavan, 1996), systemic risk (Erb, Harvey, & Viskanta, 1996) and ultimately condensing into issues of 'volatilities and stock returns' which direct impact market agents (Ahmed, Vveinhardt, Štreimikienė, Ghauri, & Ashraf, 2018). Observations of anomalies in stock index trends indicate its complexity.

The role of Market agents

Extending the outline above, the market space provides a platform for observing asynchronous actions of heterogeneous agents applying pressure to the market through choice and decision-making (Bessembinder & Venkataraman, 2010, p. 3). Using index trends for analysing these actions deliberately avoids the intricate complexities of stock markets. This approach simplifies a complex stock market system into a two-component system involving the market as the heart of a free market economy and the human element as 'free' agents driving markets through choice. This is an example of the "convergence between action and structure paradigms on a pragmatic modelling plane" (Squazzoni, 2010, p. 212 citing Squazzoni 2008). Through this view, the research problems turns into a problem of systematically observing and describing aggregate effects of agent actions on market outcomes, as a form of an agent-based model that uses real world variables. Assuming a universal validity of evidence from research on herding and information based trading (Zhou & Lai, 2009), strong aggregates of agent actions should form stronger patterns on a time-frequency plane.

Agent based modelling (Squazzoni, 2010) as a computational paradigm is another way of studying agent behaviour and analysing its effect on markets. By incorporating heterogeneity as a critical element of agents, "individual agents can be modelled to mimic cognitive and social characteristics of real world actors" including investors and agents of corporates "in terms of behavioural rules, information, resources, position in given social structures" (Squazzoni, 2010, p. 199). This conceptualisation as a natural product of social sciences has opportunities in finance and economics. Researchers agree this approach gives insights into the "problem of aggregation over individuals, in particular when these individuals are heterogeneous and their composition is dynamically changing (Chen, Chang, & Du, 2012 citing Stoker, 1993; Gallegati et al.).

Applying such agent based modelling in simulation experiments aimed at examining 'the influence of psychological character of an investor and neighbourhood on decision making and their impact on markets in terms of price fluctuations reveals observations close to real stock markets (Kodia, Said, & Ghedira, 2010). These observations include "evidence that economic actors do not have perfect access to information, do not adapt instantly and rationally to new situations, are victims of uncertainty, are not always in position to predict and maximise their long-run profit, in particular when this possibility depends upon the decisions of other actors, and are subject to such biases as overconfidence, risk aversion, and peer pressures" (Squazzoni, 2010). Such simulation outcomes agree with practical observations in research looking into information diffusion as a source of market imperfection (Ozsoylev, Walden, Yavuz, & Bildik, 2013). For example, literature has evidence of investors influencing others through their choices (Kodia et al., 2010) and cases of non-uniformity in information availability resulting from time delays in new information becoming generally known in markets (Shepp, 2002), both citations demonstrating the neighbourhood aspect of market agent psychology and socialization.

The agent-market linkage

Information is an important and fundamental connection between markets and agents. The study above of markets and role of agents in markets looking at information suggests that information has an element of direction. Information seems to propagate the market interacting with the rational and sentiment elements of its agents. This implies that rational and sentiment has a sense of direction as well. In different terms, this means that rational or sentiment can lead the process of information propagation depending on the behavioural composition or nature of interaction between market participants. There are possibilities that the orientation of these information factors underpinning market informational efficiency influence the rate of information propagation or diffusion in the market. In this, the collective effect of agents' rational and emotional directions offers an intuitive explanation for the upward or downward trajectories of index trends. The study explores this view by looking into how information can project this aggregate rational-sentiment orientation and its impact on volatility in markets.

Agent-based models portray market agents as heterogeneous actors whose individual rational-sentiment compositions are infinite, with their aggregate orientation forming visible pressure patterns on stock prices. The demand-supply push-pull dynamics on price emanating from these psychological elements are fundamental to observations of time-based stock price movements (Janse van Rensburg et al., 2015, p. 53). Around this, wavelet analysis aims to demonstrate the behavioural link between markets and agents by revealing aggregate behavioural pressures in the form of spectral classes as aggregate market trading patterns (without the concerns of the motivations on agent choices). While the use of nonparametric analysis of time series data such as signal decomposition is desirable due to its 'detachment from biases', the main challenge is interpretation (Lavelle, 2019, p. 60). Literature shows many interesting cases that struggle around this issue. Examples are an attempt by Chaudhuri and Lo (2015) to use the price signal decomposition analysis method in investigating risk as part of portfolio construction and Jun et al. (2019) in attempting to apply a similar approach as a financial crisis detection mechanism. Today, the prevalence of algorithmic trading developed markets is presenting new opportunities for looking into the rate and magnitude of trading patterns and their impact on market stability (Jones, 2013). This research study defines this challenge of clearly linking agents to markets using nonparametric analysis as the research knowledge gap.

2.2 Research knowledge gap analysis

A lot of research has gone into the problem of characterising stock markets. Literature has significant evidence of insights from research that relates in some way to the 'two most important attributes of every investment: return and risk' (Rutterford & Davison, 2007, p. 40). Erb et al. (1996) as an example studies markets using risk and its effects on future expected returns focusing on political, economic and financial risk, concluding in this instance that country-risk is a big factor to future equity returns. Other research study markets using volatility as the spread of observed investment returns in describing different market contexts (Ahmed et al., 2018; Bentes & Menezes, 2012). In general, a number of market properties such as the autocorrelation of stock price changes, the distribution of returns, heterogeneity, non-linearity, scaling, volatility, volume, calendar effects, market memory and entropy of market prices are relevant in studying markets using financial time series data (Sewell, 2011a). Along this, research on the behaviour of market participants is also emerging (Sharma & Kumar, 2019). The drive for a behavioural approach to stock market analysis is centred on 'bridging the gaps between real life situations and traditional theories' (Kapoor & Prosad, 2017), particularly when considering the increasing heterogeneity of stock market participants as the agent population increases and diversifies (Nawrocki & Viole, 2014), which is likely due to the integration of financial systems as part of globalisation.

Defining the knowledge gap

Behavioural market identity like other means of characterising markets needs to convey a useful sense of risk and return. This can encourage the broadening of the efficient market hypothesis to accommodate unique classification of an endless spectrum of markets. In this, the understanding of market efficiency continues to change. It is morphing from fixed abstractions of discriminatory efficiency classes to an inclusive and adaptive concept whose space-time-agent compositions are continuous dimensions. Supporting this view is an "expanding literature which challenges the assumed static characteristic of market efficiency" (Lim & Brooks, 2011). Around this challenge, the 'realism and descriptive power' of behavioural finance 'to a field that was originally built on perfectly rational agents and capital market efficiency' is continuously being recognised (Kliger, van den Assem, & Zwinkels, 2014).

Extending the Efficient Market Hypothesis in a manner articulated above is ambitious and broad as a goal of this narrow scoped endeavour. It appears more useful to define a more practical and equally narrow scoped target yet sufficiently oriented towards a broad goal as the research knowledge gap. Thus, the research knowledge gap is limited to conceptualising market-wide or single stock stability using systemic behavioural analysis techniques, extending ideas around circuit breakers as market protection mechanisms (Y. H. Kim & Yang, 2004). Mapping agent behaviour to market patterns provides sufficient opportunity for demonstrating the benefits of a market efficiency conceptualisation that is inclusive of all its diverse elements. In this, the vision for understanding diversity of markets from an efficiency point of view is towards creating inclusive market interfaces that support market stability and sustainable market development. Such market interfaces can also allow the management of market shocks due to extreme information flow anomalies, while simultaneously being sensitive to negative effects of market protectionism (Henn & McDonald, 2010). This logic is inverse to causal development of market efficiency and defines market efficiency as a continuous progression of randomness to order through a systemic elimination of information anomalies that violate requirements of market efficiency. If market efficiency is ultimate price transparency (Malkiel & Fama, 1970), opacity in information is the source of inefficiency.

Approach to addressing the knowledge gap

To address the knowledge gap implies adequately linking agents' behaviour to market trends, in this case using index trends as the only source of information. To this challenge, the study proposes spectral decomposition of price signals (Aguiar-Conraria & Soares, 2014) to assess if pressure patterns inherent in the price signal can reveal information structures related to liquidity and efficiency of price discovery (Riordan & Storkenmaier, 2012). In using a Fourier based-spectral decomposition technique to examine and track market failures, Jun et al. (2019) seems to adequately demonstrate that the knowledge or feeling of an impending financial crisis are detectable from the behaviour of spectral components in time series data. This reasoning supports the research thesis claiming that in addition to providing information on price movements, stock market trends embed and propagate the aggregate rational and sentiment of the market. Moreover, the meaning of this information might not be transparent to all market agents, supporting the notion of information diffusion and its behavioural consequences to agent neighbourhood based decision-making. Herding and information based trading are examples of cases that result from this type of informational asymmetry in markets (Zhou & Lai, 2009). Underpinning all this is a simple idea that market information affecting asset pricing resides within the domain of market agents, and spreads in information channels of varying dimensions at varying rates with consumption also occurring at varying rates. For example, despite information regulation information leakages occur in reality (Jiang, Zhou, & Zhang, 2018), and can create abnormal information flows that affect asset pricing associated with interesting ethical debates (Smith & Block, 2016). However, while information leakage is an obvious source of abnormal information flow, here interest rests on a net effect of information on market choices.

Part of addressing this research knowledge gap requires a relook at the efficient market hypothesis to examine its key assertions as follows. According to Sewell (2011b p.2 citing Fama,1970 and Malkiel, 1992), efficient market hypothesis states that "a market is […] efficient with respect to an information set if the price 'fully reflects' that information set i.e. if the price would be unaffected by revealing the information set to all market participants as market agents". Having extensively reviewed this hypothesis, Sewell concludes that its real world limitation is the definitional 'fully', which 'is an exacting requirement suggesting that no real market could ever be efficient, [further] implying that the efficient market hypothesis is almost certainly false'. Effectively, the efficient market hypothesis requires that information and liquidity access to be instantaneous for efficient price discovery, i.e. information latencies must be infinitesimal and liquidity infinite, which supports the view that efficient markets do not exist given present realities. However, while there could be validity to this view, it must be possible to qualify and quantify the level of efficiency in any given market by defining metrics for measuring relative and absolute efficiency. Such a contextual definition of efficiency bounds conditions for expected information flow, making it possible to detect abnormal trading patterns that violate such boundary conditions, thus offering opportunities in risk and returns forecasting. The belief here is that such a context strongly involves the psychology and social environment of the market participant.

2.3 Framework for interpreting research findings

Knowledge gap analysis builds a platform for the application of wavelet analysis by outlining the expected understanding from research data analysis as shown below in Figure 1. This expected understanding is the rational-sentiment landscape market trends can reveal about market participants' ability to determine price efficiently. The knowledge gap analysis identifies key elements defining the agent-market relationship, giving clues to how market price patterns can reflect agents' behaviour.

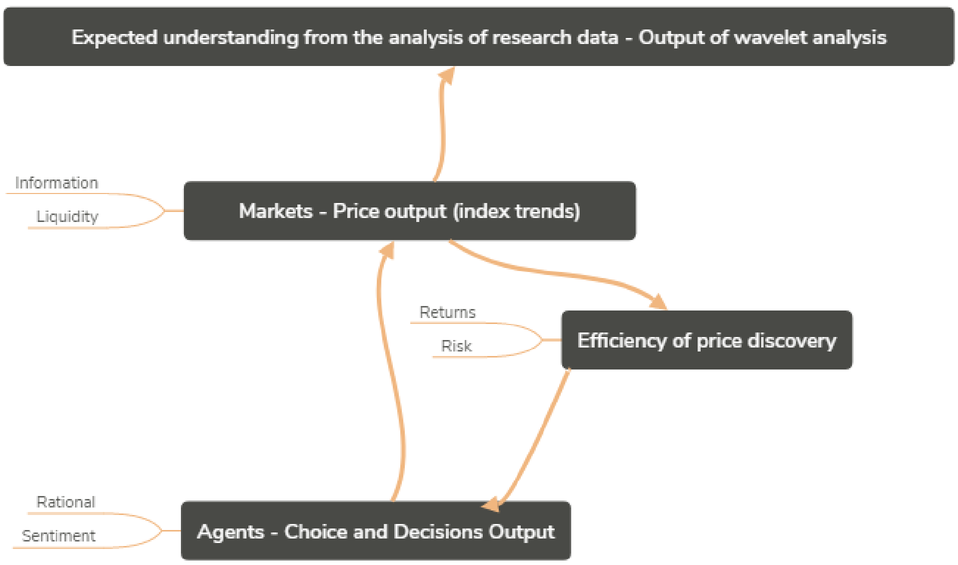

Figure 1: The connection between the market-agent links to price discovery, where the driver of efficiency is marching price to projected risk of market returns.

Formulating an interpretive framework from an efficiency point of view means connecting wavelet analysis to the Efficient Market Hypothesis. In turn, this means formulating a theoretical structure conceptualizing rational and sentiment in terms of market efficiency, then linking this structure to time-frequency patterns of wavelet price analysis. While this is an effort to detect actual behaviour and not characterize optimal behaviour (Thaler, 2016, p. 1577), in this effort the research believes that ultimately clarity on the rational and sentiment elements in information drives efficiency. The classical economic price theory argues from an empirical perspective that marginal utility as a rational phenomenon is the driver of value (represented by equilibrium price) (Weyl, 2019, pp. 343-345), the interpretive framework leans towards reductionism by arguing that the rational-sentiment plane provides a better understanding of value (and worth) as the source of pressure on price.

Support for the interpretive framework

The following evidence supports the theoretical elements of conceptualizing a rational and sentiment structure connecting agents to market behaviour:

- “A market in which prices always "fully reflect" available information is called efficient” (Malkiel & Fama, 1970), “that is, [this condition holds true] if the price would be unaffected by revealing the information set to all market participants” (Sewell, 2011b). Thus, prices efficiency affects current and future prices. According to (Malkiel & Fama, 1970, p. 387) conditions for efficiency are:
    - Transactions in trading equity are instant and have no costs
    - Information is available instantly at no cost to all market participants
- “Liquidity and efficiency are distinct concepts but there are reasons to expect a relation between [them]” (Rösch, Subrahmanyam, & Van Dijk, 2016, p. 11). “For liquidity risk, the relevant macroeconomic condition is market liquidity. Market liquidity reflects, at the aggregated market level, the ability to trade large quantities quickly, at low cost, and without moving the price (Ng, 2011, p. 127 citing Pastor and Stambaugh, 2003). Important observations about liquidity are as follows:
    - When market liquidity declines, demand for stock declines
    - When market liquidity increases, demand for stock increases

- "Higher information quality, i.e., more precise signals, lowers market risk and thus cost of capital in the traditional Capital Asset Pricing Model (CAPM) framework" (Ng, 2011 citing Lambert etal.(2007)). This implies that "higher information quality is negatively associated with liquidity risk, which is the sensitivity of stock returns to unexpected changes in market liquidity" (Ng, 2011, p. 140)
    - High information quality, liquidity risk is low
    - Low information quality, liquidity risk is high
- "Theory predicts that investor sentiment increases stock liquidity and empirical studies shows for example that a 'stock market is more liquid when sentiment indices rise, i.e., when investors are more bullish" (sentiment is high (bullish) or low (bearish)) (Liu, 2015, p. 64).
    - High liquidity is a sign that the sentiment of irrational investors is positive, and that expected returns are therefore abnormally low (Baker & Stein, 2004).
- "The information theory developed by Shannon was designed to place a quantitative measure on the amount of information involved in any communication. The theory of the value of information arises from considering jointly [the quantity of information] and economic factors that affect decisions." (Ronald. A. Howard, 1966).
    - Rational choices and information quality have a relationship (Cangelosi, Robinson, & Schkade, 1968).
    - "The rational market makers are assumed to be able to correctly infer the insider's information from the order flow while the irrational market makers are overconfident and so they underreact to the insider's information." (Liu, 2015, p. 53)

This evidence from literature gives general details of cited characteristics of rational, sentiment, information, liquidity, risk and returns around price efficiency. The evidence points out that while efficient markets have no transactional costs real world markets have "trade execution costs" that vary from one market to the other (Bessembinder & Venkataraman, 2010). In real world markets, agents use information to make choices around deploying liquidity using rational and sentiment for evaluating trading costs, expected returns and risk to returns.

Structure of the interpretive framework

The structure below connects market agents' rationality and sentiment to market behaviour using evidence from literature cited above. This structure should enable the discernment of market forms in the following manner:

1. "Measures of market activity – such as return volatility and trading volume – are directly related to the rate of arrival of information in the market." (Vlastakis & Markellos, 2012, p. 1809)
    a. High latency information is associated with a low rate of stock trading
    b. Low latency information is associated with a high rate of stock trading
2. Access to high quality information is related to market size, because high quality and low cost information "allows a rapidly growing base of investors to participate in the financial system" (D'avolio, Gildor, & Shleifer, 2001, p. 29)
    a. High rationality is associated with large markets (big indexes)
    b. Low rationality is associated with small markets (small indexes)
3. Sentiment cycles partition the market index into bull and bear regimes (Gonzalez, Powell, Shi, & Wilson, 2005)
    a. Bull markets are associated with persistently rising share prices
    b. Bear markets are associated with persistently falling share prices

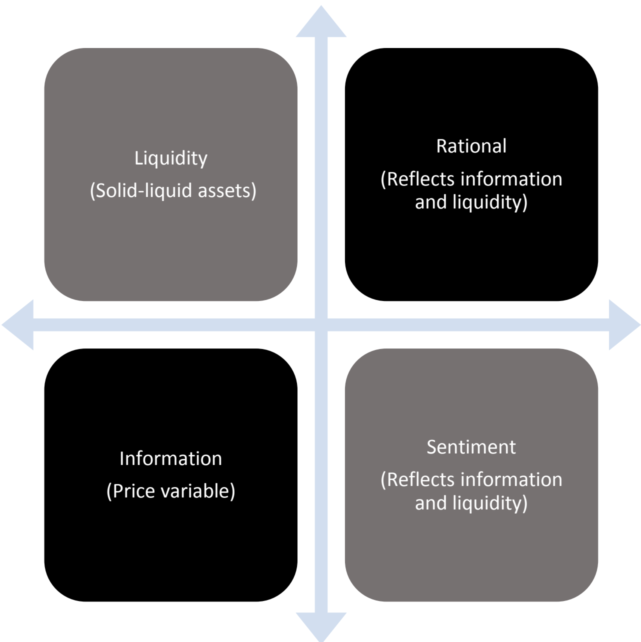

Figure 2: A simple dimension mapping construct linking agent elements to market elements. Each dimension represents a plane that can lead or lag another. Density or time can be an additional dimension perpendicular to the two-dimensional construct.

In Figure 2, information and liquidity are properties of an abstract market instance, i.e. a hypothetical market meeting some conditions of market informational efficiency. In a similar way, rational and sentiment define behavioural properties of abstract market agents. The mapping of agents' behaviour to market conditions using evidence from literature allows the formulation of a theoretical structure as bounds of causality between market and agents, as shown in Figure 2. In this structure, the orientation of each plane can be leading or lagging relative to another. For example, information can lead or lag liquidity, and an element of information or liquidity can lead or lag another. The research hypothesis is that these elements map directly to rational and sentiment implying that patterns of information and liquidity are representative of patterns of rational and sentiment.

Relationship to wavelet analysis

Establishing the bounds of market-agent interactions enables a mapping of wavelet analysis variables to information and liquidity, consequently to rational and sentiment. The wavelet transformation of a time series produces a three-dimensional image defined by variables of scale (frequency or breath in time), duration (length in time) and amplitude (correlation and phase as density and direction of an information variable or its reflection). Mapping sentiment (Gonzalez et al., 2005), information quality (Hasbrouck & Saar, 2013) and scale of trading (K. A. Kim, 2001; K. A. Kim & Park, 2010) to the three-dimensional image sets the conditions for testing the research hypothesis. Validating the research hypothesis involves testing its power in explaining indicators like market volatility, bid-ask spreads and cycles in different markets or in specific stocks in a given market.

Looking at the price index as an information signal profiling the movement of price perpendicular to the time plane (i.e. the side view) and applying harmonics with adjustable frequency and time or wavelets to this plane reveals a three-dimensional image of the price structure (i.e. as top view) in scale, time and amplitude (Aguiar-Conraria & Soares, 2014). This three-dimensional structure of information shows the elements of information width, information length and element density in time (density as the coherency and phase or the strength and direction of the price signal in time relative to wavelets). The image represents a spatial structure and its energy composition, i.e. information location and density in time as a convergence of the space, energy and time plane. Applying the interpretive framework to the information image produces the liquidity image as a reflection of price information, liquidity volume being subject to market capitalization. In this sense, strong information density can imply price withstanding market pressures and this resembles capital bound to solid long-term assets, depicting a market with long-term rational character and stable sentiment. In a case where market pressure subdues price, capital can be in liquid short-term assets suggesting that the market is sensitive to sentiment and has short term rational. An additional obscure implication of this is that liquidity can be dispersive in highly unstable markets where market pressures a great, both rational and sentiment is unstable. In this sense, dominance of rational could imply stability in economic activity and dominance of sentiment could imply turbulence.

The wavelet concept

The following short outline of the wavelet transform cites the work of Aguiar-Conraria and Soares (2014) on wavelet applications. In this outline, the admissibility constant C_ψ is a key property of the wavelet ensuring the wavelet carries finite energy. This means that the power spectral density $\Psi(\omega)$ of a wavelet function $\psi_{\tau,s}(t)$ must exist between zero and infinite. Further, the wavelet must exist in the space of finite energy functions that can be frequency and time localised. Localisation uses the Fourier frequency of the wavelet f , its dilation factor s and time shift τ.

$$\psi_{\tau,s}(t) := \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right); \;\; s,\tau \in \mathbb{R}, s \neq 0 \ldots\ldots\ldots \quad (1)$$

$$0 < C_\psi := \int_{-\infty}^{+\infty} \frac{|\Psi\,(\omega)|}{|\omega|}\, d\omega \;< \infty \,, \Psi(\omega) := \int_{-\infty}^{+\infty} \psi(t) e^{i\omega t} dt \,, \omega = 2\pi f \ldots\ldots\ldots \quad (2)$$

$$Given\, functions\; x(t), y(t)\text{: } W_{x;\psi(\tau,s)} = \int_{-\infty}^{+\infty} x(t)\psi(\tau,s)dt, \;\; W_{xy} = W_x W_y^{*} \ldots\ldots \quad (3)$$

These mathematical relationships describe the basic mechanisms regarding the design of the wavelet and its operation on time series data sets $x(t)$ and $y(t)$. In simple terms, the wavelet is an energy device for illumination the internal structure of a time signal to reveal its width, length and amplitude elements in the time domain. This research utilizes the Morlet type of wavelet for its frequency to scale conversion capability.

2.4 Summary and conclusion

Summary of literature reviewed

According to Malkiel and Fama (1970), real markets are inefficient due to cost overheads in decision making. Under real market conditions, critical factors to decision making are equity, information and liquidity. The interaction of these factors with the rational and sentiment of market agents leads to price discovery. From this depiction, asset prices in efficient markets are free from premiums involving the cost of acquiring information or the costs of moving capital in transactions. This implies that for such markets, determinants of asset prices are the internal heuristics of an agent's rational and sentiment biased by infinite information, unlimited liquidity and a wide spectrum of equity. Literature shows that real stock markets are limited in all these aspects and consequently suffer the complexity of cost. This complexity as a market overhead associated with time introduces the element of risk to future gains. Thus, risk becomes an outcome of a lack of information and or liquidity to opportunities for decision-making. In this the research suggests that the communication of rational and sentiment in market information is an important factor to the miss-match of opportunities and decisions, a requirement for outperforming a free market system.

The theoretical structure conceptualizing rational and sentiment in relation to stock market behaviour focuses on basic components of a market systems and their intuitive interactions. A stock market system comprises of the market as an entity and market participants as agents. Important participants groups are investors and corporates and their basic activities involve buying and selling of equity, motivated primarily by expected returns in this. As the basis for decision-making, trade on equity requires capital, equity itself and information to enable projections of returns against risk. An attempt to establish motivation for trading broadens the term return to involve any nature of return that a market agent might seek from stock market trading, and the risk associated with its attainment (i.e. in present realities everything has a price and a cost). Looking at stock market interactions in this manner enables a mapping of information and liquidity as dimensions of market realities to rational and sentiment as dimensions of agent behaviour. Literature concludes presenting a method for analysing and interpreting this link using the wavelet transformation of price signals.

Proposed research strategy, design, procedure and methods

The fulcrum of the research hypothesis lies on the intuition that ultimately human behaviour determines market behaviour. To give weight to this view, this research forms a simple quantitative argument that uses tools from the scientific method to analyse data and pragmatism to interpret the analysis in a qualitative manner. Applying quantitative data analysis aims at quantifying ideas around this intuition without attempting a detailed and systemic conceptualisation. Thus, this approach is a pragmatic application of objectivist and interpretivist research paradigms justifiable in this research for the selected business stance and complexity of the problem. Business contexts involve complex interactions of variables that would be difficult to understand from a purely objective perspective. Because of this, the research places value on interpretation as opposed to theory formulation. The intention of this approach is to develop a plausible interpretation of the research analysis based on credible and dependable methods, and assessing the validity of the interpretations using other observations on market signals.

The research strategy integrates the causal approach of experimental research in real life market cases. Using market cases as real life experiments produces practical research outcomes that might be transferable to other similar market cases. Primary research data is observational data forming the live JSE and LSE stock market trends. This data is publicly available and easily accessible. Data analysis is primarily quantitative using wavelet transformation as the analysis technique. The research uses this technique to transform stock market price signals into their frequency components, in scale and phase. The proposed interpretive framework is then applied to tests the hypothesis. Research validation of the hypothesis uses a basic form of correlational analysis of stock trends and volatility. This establishes thematic correlations of outcomes from trends analysis and volatility signals as market observations.

3 RESEARCH STRATEGY, DESIGN, PROCEDURE AND METHODS

Research methodology attends to the second research objective that outlines the philosophical framework as a platform for time series analysis. This framework follows quantitative elements in using numerical data processed by the continuous wavelet transform (CWT) to provide a time-frequency resolution of stock market price signals. The interpretation of the analysis on the other hand adopts creative thematic analysis that applies mapping of market and agents variables. Research design follows a case study approach where different stock markets and their contexts present cases of natural experiments, supporting elements of causality in pattern analysis. In this, stock market price signals as observed outputs from these markets form the research data, each dataset representing market instances on the market-efficiency continuum. Stock market signals are easy to collect, store and process without any special measures, ethically or otherwise, which simplifies the data-collecting instrument. Detailing the methodological approach to interrogating the ambiguity in the research question as outlined below is the main measure to consider. Establishing the knowledge context around the research data is necessary as it supports data analysis, interpretation and conclusions. The research selects objective methods in data analysis while providing room for creative interpretation of analysis outcomes. Selecting this methodological framework seems justifiable given that business context variables are obscure and where visible they are difficult to explain as seen in literature review. In carefully defining contexts, the research takes a context-based stance while attempting some universal projections.

3.1 Methodological framework

The methodological approach to the research as a research strategy is "consequential to the researcher's philosophical stance and the social science phenomenon to be investigated" (Holden & Lynch, 2004, p. 397). The social science phenomenon studied here is inherently complex as it involves human behaviour in an ever-changing business environment. The business context introduces complexities that affect analysis of stock markets due to economic ecosystems with increasingly permeable geographic boundaries. On the other hand, there are no clearly defined rules that describe human behaviour in the research space. Attempting to establish structured knowledge from this scale of complexity is extensive and to avoid this obstacle, the research takes a pragmatic stance in defining simple conceptual spaces devoid of detail and projecting expected behaviour based on broad assumptions. The research hypothesis contends that behavioural elements in these conceptual spaces will behave in a similar manner to real market spaces. This is an attempt to draw the best from positivists and interpretivist stances (Ryan, 2018), as specific cases of objectivism and subjectivism (Holden & Lynch, 2004, p. 399). Arguably, objective research into human behaviour by a human is bound to be subjective. "[This is the] impossibility of 'complete objectivity' or 'complete subjectivity' in conducting research" (Kankam, 2019 p.86 citing Tran, 2016 p.10). Here, the research ambition consequently is towards likelihood and not certainty.

The research stance

The philosophical principle of pragmatism guides the research path as a paradigm that embraces the diversity of philosophical views. In this, pragmatism offers flexibility needed to tackle the complexity in this research and leaving the definition of 'what works' to selective elements from paradigms guiding research in the two dimensions of society and science (Hall, 2012, p. 5; Holden & Lynch, 2004 p.397 citing Burrell and Morgan 1979). With pragmatism, "research design and methodology may take a multitude of forms including quantitative, qualitative, and mixed methods research depending on what the research judges will most effectively produce a warranted assert-ability of knowledge claims given available data, possibilities for analysis, and available resources" (Biddle & Schafft, 2015, p. 5).

Analysis and interpretation of research

This study uses an ontology of realism in conceptualising behaviour by projecting agent behaviour as a construct constituting an indeterminate composition of inseparable rational and sentiment elements. Nominalism bounds this proposition by defining the existence of pure rationality on one end and pure sentiment on the other as true universals. A similar projection structures market information and liquidity, (solid) information and liquidity are true universals. This forms the ontological space for examining behaviour. The research fragments the epistemological space by allowing objectivism in procedures and methods while accommodating elements of subjectivism in the research design. This presents the mental model of the research primarily around a scientific approach while acknowledging the simplification of its subjective elements in a way that affects the interpretation of outcomes, particularly the transferability of conclusions.

3.2 Research strategy

The strategy for this research is its direction from paradigm to approach (Mertens, 2012) and this paradigm to approach defines using what is understood to reveal what is not understood. Consistent with the outline above, this involves using objective quantitative methods in research data analysis and presenting its results in a qualitative interpretive framework. Quantitative analysis presents a natural research strategy for time series analysis. The object in this time series analysis is to decompose a time related price or returns signal and reconstruct it in a two or three-dimensional sense using the continuous wavelet transform. This two or three-dimensional image reveals frequency patterns (their amplitude in the case of a three dimensional view) and the time localization of the frequency components. Key variables under observation from the research data are the scale-localisation of frequency components (width of spectral components), the time-localisation of frequency components (length of spectral components) and intensity (or density) of the spectral components (depth of spectral components – presented by colours as an outward projection).

3.3 Research design, procedure and methods

Research design marks the transition from the research's mental models to practical real world scenarios involving data and its analysis by clearly defining the contexts of research including mapping domain variables to analysis variables. Here, 'general procedures of research called strategies of inquiry' connect the 'philosophical assumptions about what constitutes knowledge claims' to the 'detailed procedures of data collection, analysis, and writing, called methods' (Creswell, 2012, p. 3). In this study, a case study approach involving two stock markets, the Johannesburg Stock Market and the London Stock Exchange, provides this connection.

Application of the case study design

A case study provides a research path from design to creation and data generation to data analysis to realise the philosophical frame outlined above. In this sense, each stock market forms a unique natural experiment case with associated quantitative data collection and analysis. Using experimentation enables the application of the continuous wave transform as a quantitative analysis technique commonly applied in science. The continuous wavelet transform is objective as a mathematical analysis method; however applying it to instances of differing market contexts unavoidably introduces subjective elements or context specific biases. By defining the ontological and epistemological spaces as outlined above, the research attempts to highlight subjective factors due to context in order to isolate universal ideas.

While each market economic context is unique, agents are consistently human actors across contexts, and market properties (of information and liquidity) have a consistent function too. The cause and effect as consequence of real-world interactions of these factors can then possibly explain variations between markets in terms of diversification of indexes, volume, order processing, economic development and risk appetite amongst other context specific details. Thus, the main object of a case study approach is to treat each market as a unique entity due to inherently many micro differences between markets but drawing attention to common aspects in the market cases.

Each case as a unique experiment

Given that the primary concern of the research is around the likelihood of discerning stock market agents' behavioural orientations from index price trends, the visible elements of causation justifies an experimental approach. There are possibilities that price affects behaviour and behaviour affects price through a simple and obvious consideration that market agents act to generate and consume price information. While the argument here is that any market condition propagated in market information primarily interacts with market agents' decision-making heuristics before affecting price, the very presence of decision heuristics makes it difficult to establish causation (Hensher et al., 2005, p. 62). Moreover, due to the real world nature of the problem, the difficulty in manipulating real world variables limits studying causation using experimentation.

Experimentation requires the ability to manipulate research variables in this case being in the form of the stock index as a price variable, agent behaviour as a composite variable with rational and sentiment dimensions, information, equity as traded articles, liquidity and the market construct. Thus, this inability to manipulate these variables limits a full positivist stance in design.

Emerging agent based models of stock markets (Chen et al., 2012; Steryakov, 2012) are an effort to address these challenges of studying causation from similar enquiries. Improvements in computational techniques have improved prospects and insights from such studies, particularly re-enforcing issues of agent heterogeneity and stock market asynchronous dynamics with many such studies mostly interested in prediction. Outside creating and using computational models in conceptualising the real world as offered by these approaches, this research looks at opportunities in real-world contextual understanding of stock market phenomenon. For this reason, research design justifies the choice of a case study approach as a means of accommodating real world perspectives in interrogating the research question. This design stance is further qualified as a combination of natural experimentation and interpretive sense making. This means that "the explanatory logic of the case study shares many features with [a] laboratory experiment", where however "establishing cause–effect relationships is regarded as 'simplistic' in the face of complexity" (Welch, Piekkari, Plakoyiannaki, & Paavilainen-Mäntymäki, 2011 p 746-7 citing Stake, 2005, p.449). As an alternative to manipulating variables, the research takes two market cases as naturally occurring experiments with real variables.

Research procedures and methods

Stock market index data from the JSE and LSE is quantitative, public and ethically accessible. On its own, such accessibility (in the subjective measure of this study) indicates some level of positive bias in the efficiency direction of these markets since availability of price signals in highly structured electronic form implies ease and speed of processing. Imposing the concept of natural experimentation on markets implies that the market function as a data generating function is the data-collecting instrument that produces quantitative observational data. This instrument is some mechanism that traces information on a time scale.

While a number of methods can perform time series decomposition, the choice of the wavelet transform in favour of the Fourier approach owes to limitations of the Fourier transform in dealing with some properties of financial time series. These properties include non-stationarity, non-linearity, non-independence, momentum and fractal patterns in data. Citing Lavelle (2019), "the Fourier transform has often been that tool to provide further insight into the frequencies that are present in the input [time] series", the problem with it however "is that it assumes that the strength of these frequencies do not change over time; it assumes a stationary series". Thus, "the most common argument to justify the use of wavelet analysis over Fourier analysis is that with wavelets the power spectrum is estimated as a function of time, tracing changes in the structure of the data generating process" (Aguiar-Conraria & Soares, 2014, p. 346). In other words, wavelets sample the structure of a data generating process at multiple points in time to reveal its form, on the other hand the Fourier transform samples from its beginning to its end, which is undefined for an infinite series (or an unending data generating process) causing limitations in image resolution.

The wavelet transform is thus recommended in such situations where drawbacks of the Fourier transform are clear (Kılıç & Uğur, 2018). For this reason, the wavelet transform is finding more applications in stock market analysis around pattern identification, locating discontinuities in patterns, signal filtering and forecasting trends. A particular common application of wavelet financial-signal filtration allows the 'de-noising of price series [to] detect the level of rationality in a market and enable '[understanding] the impact of rational strategies on stock markets' (Lai & Huang, 2007). The key to the capability of wavelet transformation is the ability to vary a wavelet's periodicity (i.e. scale or frequency) and amplitude then penetrating an information structure to reveal its scale and amplitude dimension in time. In this, the wavelet transform is a mathematical x-ray of an information structures whose profile is visible on a time line. In the transform process, a wavelet transform function projects seismic wavelets of finite energy onto the information structure illuminating it into a three-dimensional image.

The time-frequency resolution of the continuous wavelet transform (CWT) is more useful for this study compared to the discreet wavelet transform (DWT) due to its wider spectrum. A better spectral resolution of signals can reveal better clues around the outlines of shapes, which helps link market trends to decision horizons of market agents. Decision horizons as directions in width, length and amplitude information dimensions of time indicate a collective ability of market agents to create information structures in time and their ability to hold these structures in place. Ultimately, efficient markets are markets that exercise greater control of choice in the market direction, its rational and sentiment through understanding time using the spatial and energy dimensions of information. Hence, "mathematical transformations are applied to time series to obtain […] information that is not available in the original time-domain series" (Lai & Huang, 2007).

Capabilities of the wavelet technique

Signal decomposition based quantitative analysis methods that use wavelet are increasingly popular. In a paper that highlights the benefits of the continuous wavelet transform (CWT) in economics, Aguiar-Conraria and Soares (2014) demonstrates various features of the continuous wavelet transform for quantitative research strategies. The general idea behind wavelets as mathematical tools is their ability to scan time series data to reveal its multi-dimensional information structure. The output of wavelet transformation is an interesting transition from quantitative forms to qualitative ones. In this, a major difference between CWT and DWT techniques is the resolution or clarity of the qualitative forms they produce. Aguiar-Conraria and Soares (2014, p. 345) emphasizes on this by remarking that "the [images] obtained with CWT [continuous wavelet transform] are much easier to interpret than the results obtained with DWT [discrete wavelet transform]". While on its own this statement provides support for the CWT over the DWT in agreement with the research strategy, in the domain of pragmatism it is also evidence of a quantitative-qualitative transformation stance that enables viewing of complex data as simple images. The wavelet transform produces an analysis output in vector formats too complex to understand without some visualisation mechanism. For this reason, the wavelet transform as a tool for analysing time series data provides an interesting interface between objectivity and subjectivity, which suggests that an objective-subjective stance maps to a quantitative-qualitative stance. Thus by understanding the interpretation of its subjective elements, wavelet analysis produces an image clear enough to generate an objective understanding of real world scenarios. Towards this, Aguiar-Conraria and Soares (2014) look into a number of applications that involve the wavelet transform relevant to this study.

Application scenarios outlined by Aguiar-Conraria and Soares (2014, pp. 346-357) involving wavelet analysis and cross-wavelet analysis guide procedures and methods used in this study. These procedures and methods apply the continuous wavelet in transforming single time series data set and the cross-wavelet transforms to correlate a pair of time series data sets using a single image. Using these transformations to explain markets as information and liquidity structures related to agents' market behaviour presents evidence for accepting or rejecting the research hypothesis. In particular, the cross-wavelet form attempts to validate the hypothesis by showing how market volatility reflects a misalignment of investment strategy or market direction to apparent or obscure information, i.e. information horizons and their effects on the market agent choices in deploying liquidity. In this sense, a market crisis is the emergence of new market information that creates deviations on expected returns from known projections, and this should be visible from a cross-wavelet transform of price trends and dispersion of returns. The desire to detect these scenarios justifies the choice of using the wavelet transform in supporting the broad research goal of presenting market efficiency as an infinite concept driven by information and liquidity.

3.4 Research strengths—reliability and validity measures applied

Ihantola and Kihn (2011) offer insights into issues on research validity and reliability that this study. The significance of these issues is their bearing on the quality and nature of research conclusions possible from this study, considering its quantitative and qualitative elements. In the quantitative sense, reliability refers to "the consistency of the analytical procedures" and validity refers to "the precision in which the findings accurately reflect the data" (Noble & Smith, 2015, p. 34). "[Measurement] and internal validity as an issue between logic and theory, as well as evidence and phenomenon" (Ihantola & Kihn, 2011 citing Arbnorand Bjerke, 1977, p. 217, Ryan et al., 2002, pp. 155-6) is addressed using pragmatism. Adopting a pragmatic stance reflects complexity in the subject where a clearly documented consistent theoretical view is not present, hence the application of both deductive and inductive thinking. This approach offers the flexibility necessary within a time-constrained research. In this pragmatic stance the research leans to the strengths and clarity of the research tool in an attempt to "compensate the weaknesses of one method with the strengths of another method"

(Ihantola & Kihn, 2011 citing Onwuegbuzie and Johnson, 2006). As already pointed out, the wavelet transform as a refinement of the Fourier transform is a remarkable and more objective research tool for analysing non-stationary time series (Norsworthy, Li, & Gorener, 2000). In using certainty to understand uncertainty, plausible interpretation fills the gap between logic and evidence, theory and phenomenon, which can map the measurement and internal validity of the tool to the credibility and reliability of interpretation.

Around the challenges articulated by Ihantola and Kihn (2011, p. 42) of external and ecological validity in research methods as a route towards generalisability and transferability of research conclusions, the research takes the following measures. First, the research identifies constructs in the study and their common properties as universal variables. In line with this, the research models market agents are human actors describable by some abstract composition of rational and sentiment. In the case of stock markets, the research presents them as platforms where information and liquidity form the basis of trade in equity towards earning returns. To reflect real world realities, the research demarcates these universals using a case study approach to accommodate contextual factors, then in each case simulating natural experimentation to investigate elements of causality. The second aspect to preserving integrity is the selection of a research instrument offering context independent quantitative analysis of the 'experimental' data consistently across cases. These two measure in combination enable the use of the same interpretive framework across cases creating a common meaning for the research outcomes with some potential of generalisations.

3.5 Research weaknesses—technical and administrative limitations

The main limitations of the research emanate from contextual factors. While the research can make some valid assumptions about agent behaviour across market spaces, factors of beliefs and culture might have a bearing to local market behaviour (Atmaz & Basak, 2018; Brandon & Wang, 2012; Hörner, Lovo, & Tomala, 2018; Sohn & Sornette, 2020).This limits the ability to compare market behaviour using the same measures and generalising or transferring conclusions to other markets.

4 PRESENTATION OF RESEARCH RESULTS

The research proposes a wavelet based method for examining insights about the mind of the market or its elements of character from stock market time-trends. In a pragmatic frame, the wavelet method presents unique opportunities for revealing complex information structures in simple data sets around this. Applied to stock market trends, the wavelet transform takes a two-dimensional information-time vector and converts it into a three-dimensional vector projecting information structures on a time plane. The projected structures have length, width and height elements forming pixels or frames in a time image. In this study i.e. in the results below, colour and its intensity represents boundaries of structures based on information strength or density. This research attempts to use these information projections to apply the formulated interpretive framework in assessing the minds of market agents, arguing for plausibility of the research hypothesis. This hypothesis claims an elementary connection between liquidity, information, sentiment and rational, and examines the interaction of these elements in a practical sense using the stock market as a model of a free market system.

Using the wavelet transform for this task is fitting given its time localisation capabilities in multiresolution analysis of time-energy signals. Considering the business context of this research, emphasis on the tool may overshadow the philosophical dimensions of the presented claims. Thus, in creating the data analysis environment, attention on mathematical operations of wavelet analysis is intentionally minimal save for its identification as a mathematical artefact. A larger part of the research attends to philosophical implications of signal decomposition, examined here by way of example using stock market trends. The implications have intuitive applications in business, where market analysis using wavelet images turns science to art.

Presentations below attend to these implications using wavelet transform images. The internet is the source of the input data to wavelet analysis and this data is available for download at the location **www.investing.com**. Data from these indices is public information, and its use in this kind of research is ethical. Analysing this data involved running a computer program using a wavelet toolbox by Aguiar-Conraria and Soares (2018) in a Matlab software environment.

4.1 Wavelet analysis of stock market trends

Recapping parts of literature review, stock market trends are observations of an aggregate price variable at particular time intervals (i.e. on the profile of time or length side of time). These observations form a profile of the information variable at time locations when projected onto a graph. The wavelet transform scans this two-dimensional vector to reveal an additional time axis (the width of time, periods or reflection of time). Information in time then becomes a vertical projection sitting on a time plane, thus forming a three-dimensional structure. Vertical projections from the time plane as the height of information elements represent protrusion, visibility or the density of information on the time grid. In the statistical images below, the colour blue represents sparsely dense information and red represents very dense or solid information, the solid-liquid information axis in the interpretive framework. The wavelet transform scans this axis at every period and length using wavelets. The resulting image reveals the market information structure to a given resolution. Mapping rational and sentiment to this provides a way for the research to interpret market movements from index price trends using shifts in the mind-set of the market. Using this, localisation of bad market behaviour along the rational (sentiment) axis is possible, and an analysis of the 2008 market crush demonstrates this.

Behavioural patterns in the Johannesburg and London stock markets

The following results present evidence towards the research hypothesis as follows:

- Description of market structures using information and liquidity then mapping these to rational and sentiment. This uses monthly- average index trends for 20 years to accurately assess market cycles of around 10 year periods (applying the Nyquist sampling law), which forms a reliable 10 by 20 year time grid.
- Exploring a relationship between index trends and market volatility using wavelet coherence analysis. Coherence analysis examines similarities in phase, frequency and waveform between two signal sources. Here, this analysis examines similarities between information structures around the price index and volatility of returns.

Spectrum analysis: Indices wavelet projection

The wavelet power spectrum in **Figure 3** and **Figure 4** is an image of information density pixels in a time grid. The time grid has elements of width (time-periods) and elements of length (time-duration). Each time pixel as an element of this grid contains information in a moment (cycles of time and their protrusion above the time place), this information being belief in some element of rationality or sentiment about the market. These beliefs represent elements of certainty in information artefacts. In this manner, the index wavelet analysis projects market belief patterns, and the strength of market rational and sentiment elements in these beliefs forming its solid-liquid structure.

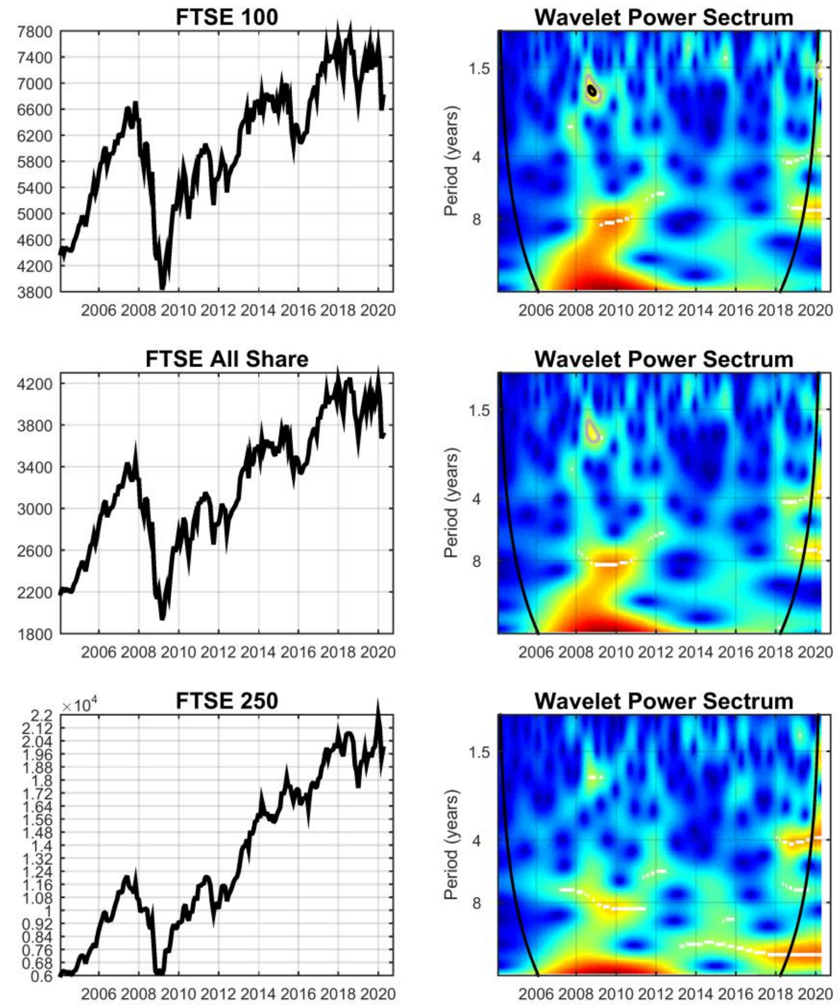

Figure 3: FTSE indices together with their wavelet transforms. Here, a 2008 market bubble appears strongest in the FTSE 100 index in terms of intensity and time horizons.

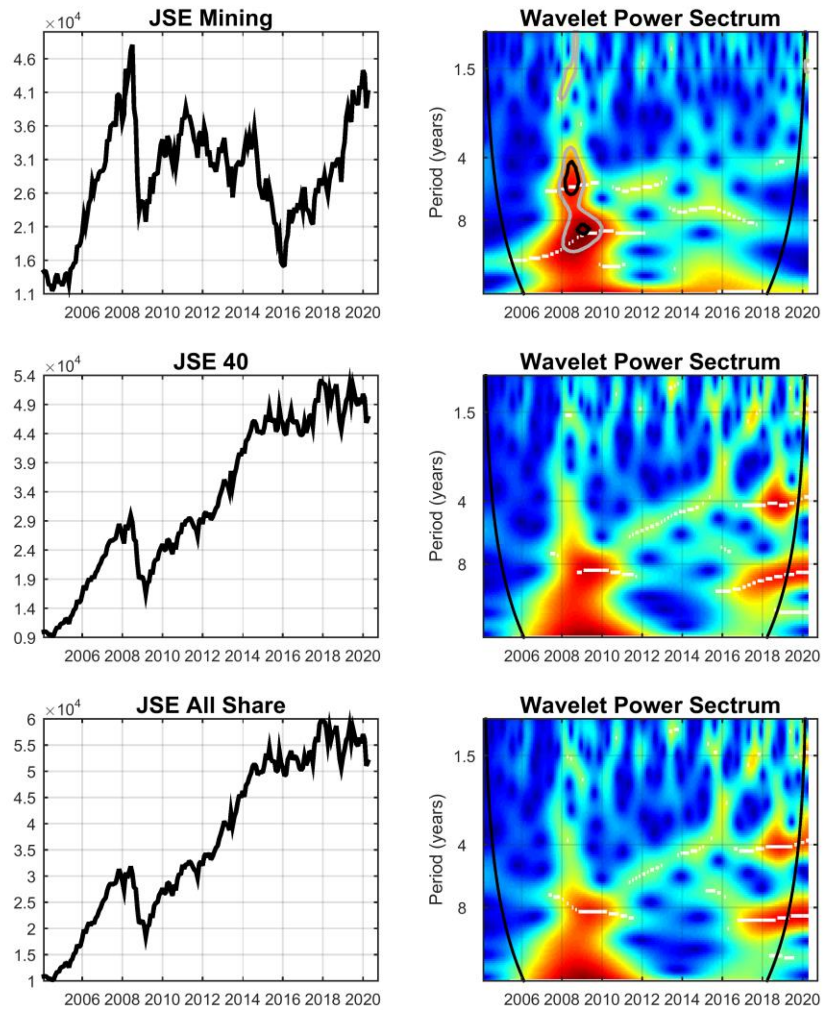

Figure 4: JSE indices together with their wavelet transforms. Here, new market beliefs appear to be forming in the JSE top 40 and all-share indices suggesting some market restructuring.

Applying the interpretive framework to compare wavelet images of Johannesburg and London indexes in **Figure 3** and **Figure 4** shows clear similarities in structures of market belief. There is an ability in both markets to hold long-term beliefs, which can translate to market information efficiency enabling market agents to see broader market horizons. A case in point is in the power spectrum of the JSE Mining index, which shows strong long-term market beliefs in 10 to 12 year horizons. This suggests to some level solid rational around the mining industry in the Johannesburg market in a similar way the London market believes in its Top 100 index. **Figure 3** and **Figure 4** cannot however compare the sizes of such belief structures.

Descriptive statistics: FTSE and JSE Synchronisation

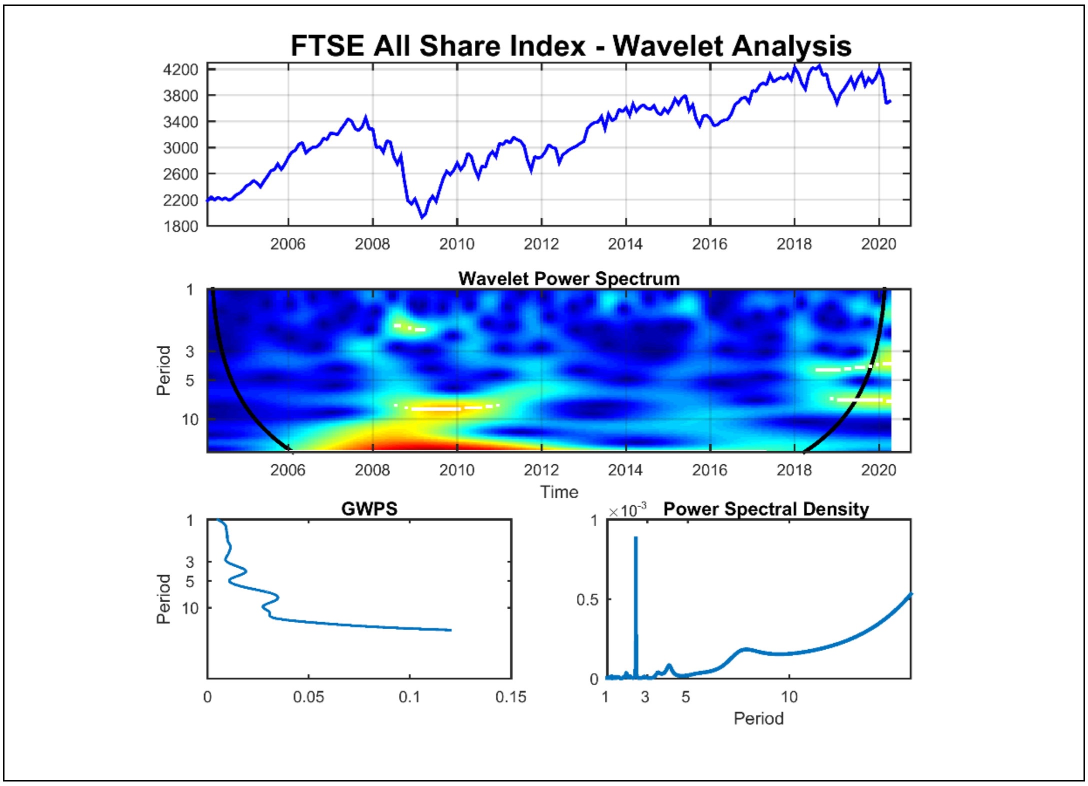

Figure 5: The FTSE all share index time trend together with its wavelet transform, the global wavelet power spectrum (GWPS) and Fourier power spectral density.

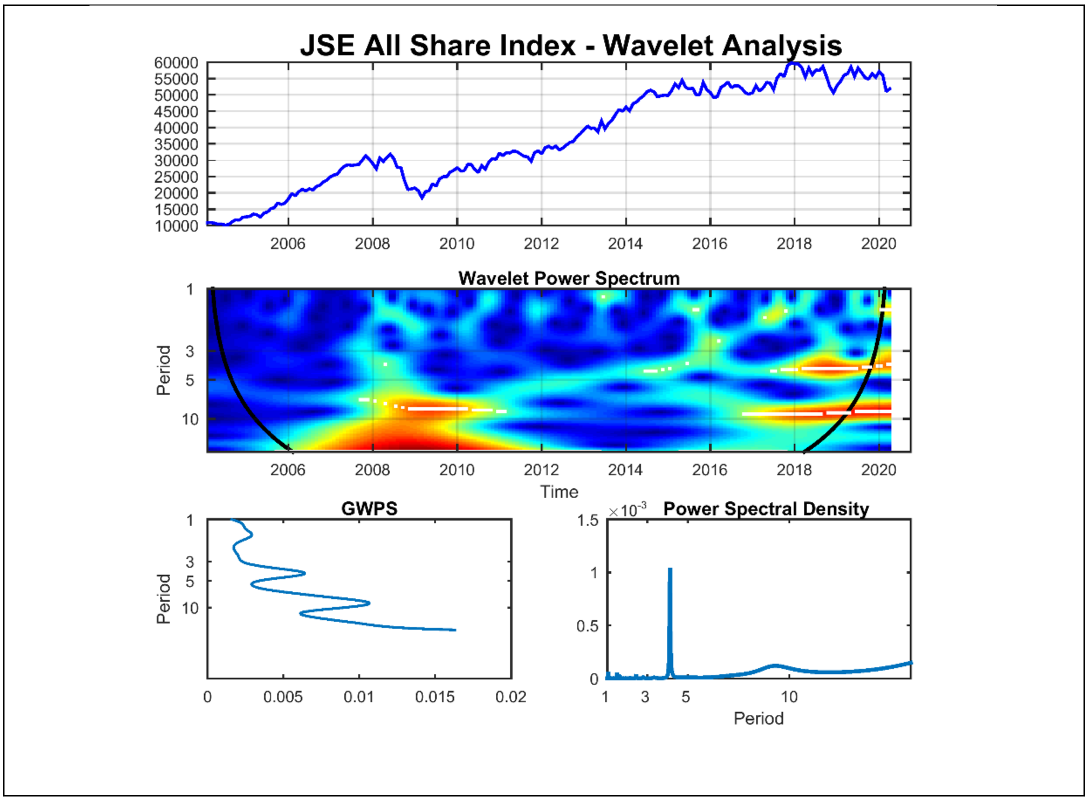

Figure 6: The JSE all share index time trend together with its wavelet transform, the global wavelet power spectrum (GWPS) and Fourier power spectral density.

Coherency analysis (**Figure 7**) confirms synchonization in rational and sentiment between the Johanessburg and London markets (**Figure 5 and 6**), with small lead-lag differences. While this research primarily uses the wavelet transform, the Fourier transform is introduced in this analysis to demonstrate a weakness of the wavelet transform. Comparing the Fourier power spectral density to the global wavelet power spectrum (GWPS) of the FTSE and JSE global indexes reveals an interesting lead-lag scenario. Here, the GWPS is unable to detect a temporary sharp spike in information density around 2008 which behaves differently in the two markerts. In the London market this spike has shorter horizons than in the Johanesburg market. The spike occurs in step with a 2008 market down turn which is visible from the time trends. Coherency analysis gives a number of possibilities around conceptualizing efficiency and stability using such information structures. For example, while it is visible in **Figure 7** that information patterns between the Johanesburg and London markets generally overlap, questions can be asked about origins of spikes and their duration in the two markets.

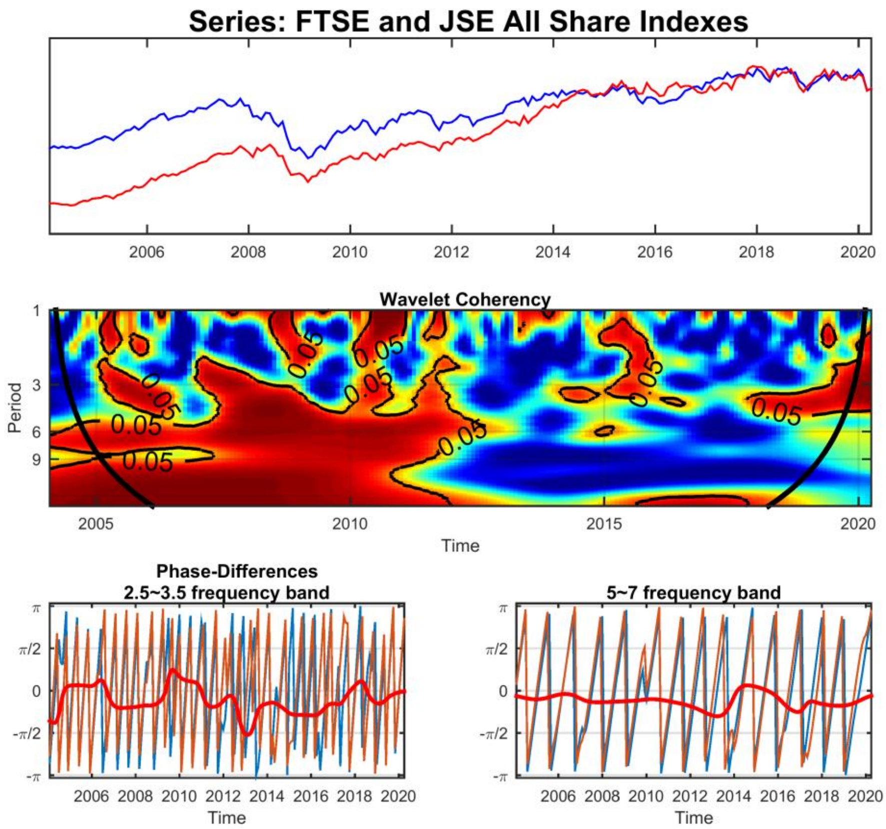

Figure 7: A similarity analysis between the FTSE and JSE index trends using their wavelet coherency.

Descriptive statistics: FTSE and VIX Synchronisation

Figure 8 shows a comparison of the wavelet power spectrum of the FTSE 100 index and the VIX, its volatility measure.

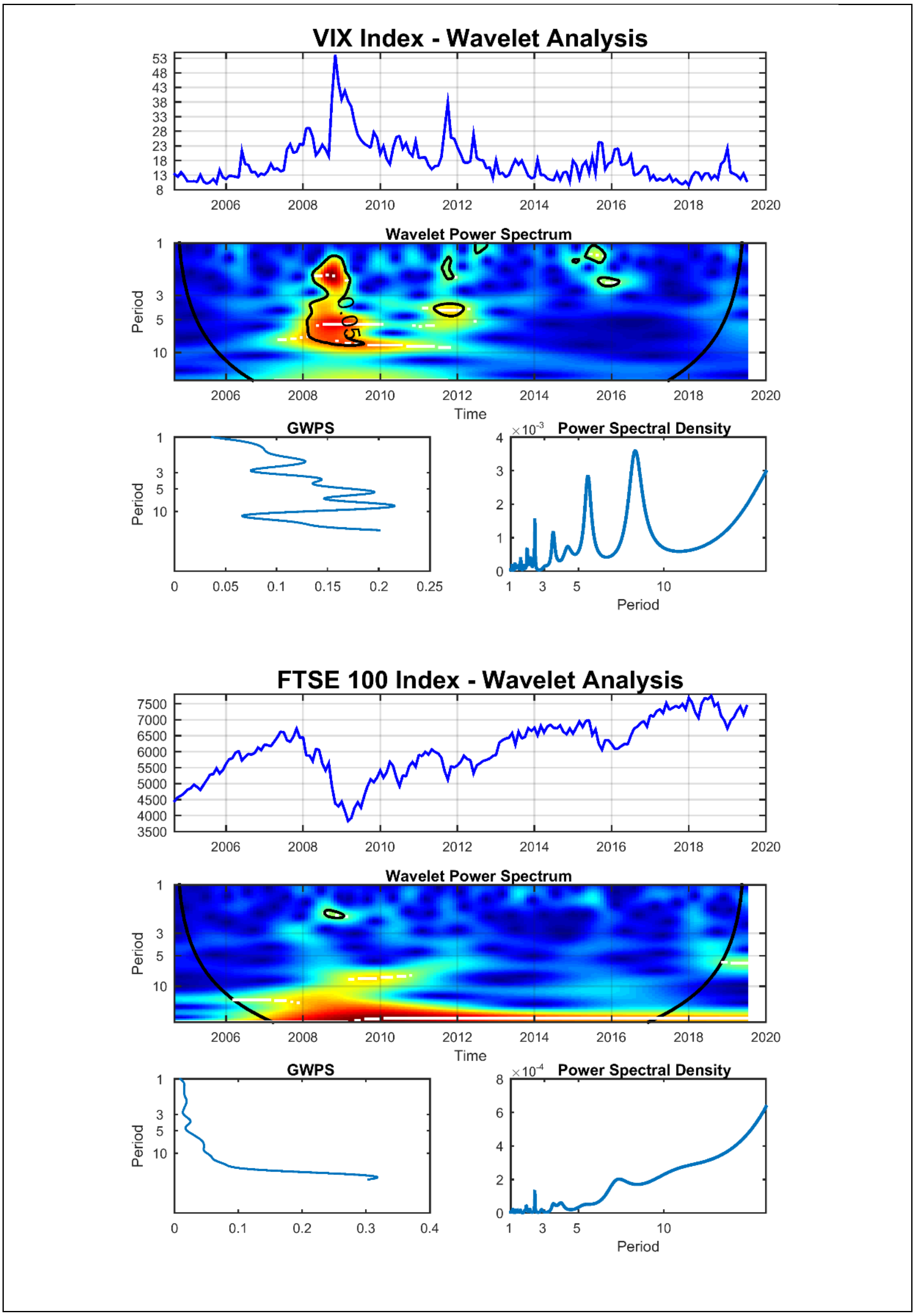

Figure 8: The FTSE volatility-index time trend together with its wavelet transform, the global wavelet power spectrum (GWPS) and Fourier power spectral density.

Figure 8 helps examine the relationship between stock market price trends and volatility. In this figure, a number of relationships in the information structures of the two market signals are visible and they mark market events in given time horizons. These horizons are the width and length of the time grid in which the market events occur. For example, the FTSE 100 shows a window of sharp frequencies in 2008-2009 within 2 to 3 year periods. This information spike coincides with the epicentre of a volatility window starting in 2008 to 2010 with strong 2 to 10 year periods. This volatility window sits in a strong market information structure starting in 2007 ending in about 2013, with strong periods in the 5-10 year range. Wavelet coherence analysis superimposes such windows to identify coinciding data patterns. **Figure 9** shows such a superposition producing the wavelet coherency image. This coherency image reveals a strength of the wavelet method in analysing data with time-limited oscillations. The coherency image enables the identification of market cycles most affected by market spikes. Applying this insight to the event in the 2008-2009 time-window makes it possible to see market cycles misaligned to projected risk-returns due to rational (and sentiment) spikes. These are cycles where belief is lost as markets change.

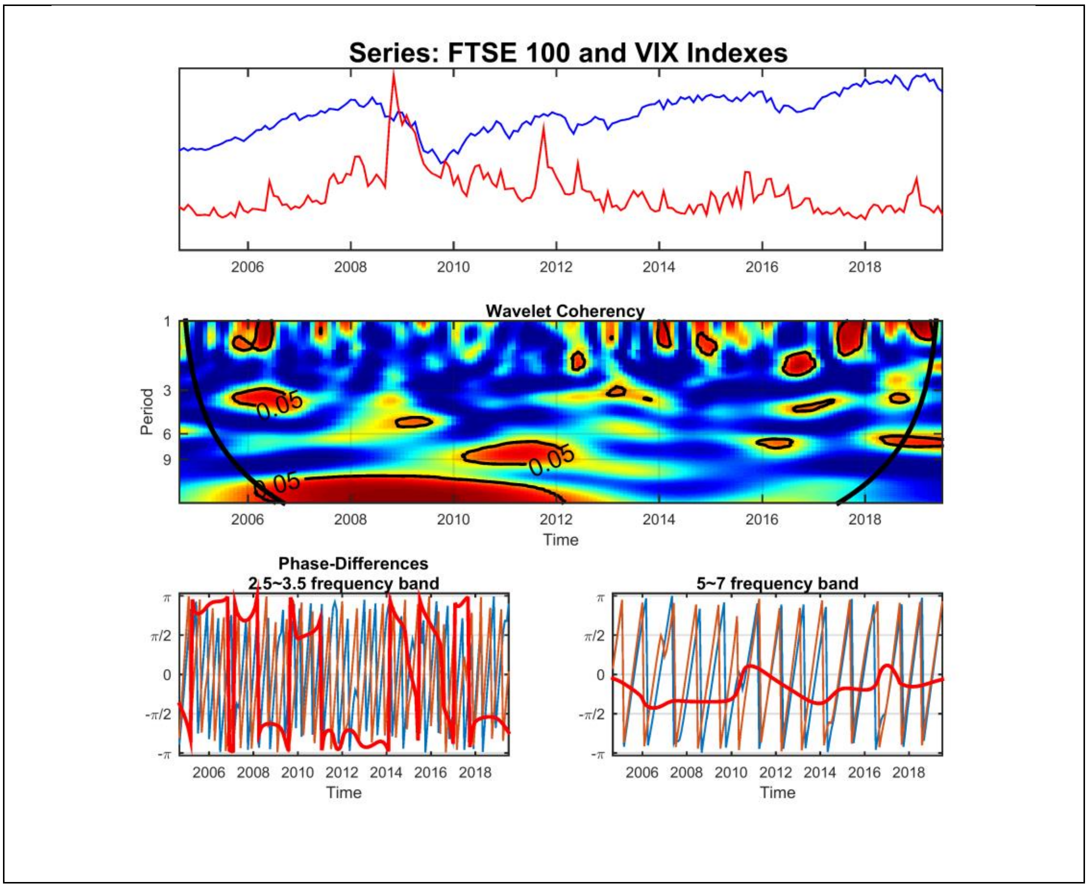

Figure 9: A similarity analysis between the FTSE All Share and VIX trends using their wavelet coherency.

Hypothesis evaluation: Agents-market mapping

The research hypothesis raises possibilities of using time series data to examine the minds of markets. In a practical sense, the hypothesis suggests a possibility of using index price information to project an information-liquidity image that can help understand market aggregate rational and sentiment, particularly towards understanding unique market events. Accordingly, the interpretive framework, by reasonable extension, claims that information and liquidity are elements of a spectrum on the axis of worth, elements that map onto a rational-sentiment axis of value. This perspective suggests that the price of an asset is its worth to one market agent which is equal to value in the cost of acquiring it by another i.e. price reflects the rational and sentiment of both agents. As articulated in literature review, evaluating this hypothesis requires the following conditions to be valid:

- That free markets are platforms for generating gains using rational and emotions
- That volatility measures stability of market platforms using variations in gains
- That price index information is a time shifting equilibrium of market forces

Applying these conditions to scenarios discussed above shows a visible relationship between information structures in the market mind-set and market volatility. The 2008-2009 market financial market disturbance illustrates this by showing some change in the market price structure causing market volatility. Here, a price information structure appears unexpectedly in the mind of the market and the market subsequently experiences some volatility. Further, the location in time of the source of volatility shocks and their intensity gives ideas about market risks prevailing in that timeframe. From this it would seem that for a market with a prevailing returns structure, the magnitude of information disturbance and its location in time (i.e. risk profile of a given market time structure) determines the levels of volatility. The correlation of the volatility epicentre and a sudden protrusion of a new information structure shown in **Figure 8** is evidence supporting the research hypothesis, revealing possibilities of localising market information problems within timeframes or pixels. This localisation is dependent on the quality and depth of information in a market. This is quality and depth of information that can enable the isolation and understanding of psychological energy, its propagation and impact in markets as a scientific basis for defining market efficiency.

Comparisons of results to other similar studies

"Several questions about economic time series data relate to their behaviour at different frequencies" (Aguiar-Conraria & Soares, 2014, p. 344). Many economic studies examine this behaviour in markets and attempt to attribute human elements to it. While certain outcomes of this examination are unique to this study, other studies confirm important aspects of it that re-enforce the general direction of this research. The table below shows some of these aspects as extracts or comments from similar studies. These comments provide evidence outside this discussion confirming the existence of key pillars supporting the research hypothesis. These pillars support linkages of an identifiable human-market relationship around price information. Evidence below confirms that human habits and behaviours are the drivers of markets, that multiresolution analysis creates the possibility of using mapping to project information on a time plane to examine these human habits and behaviours in understanding market phenomenon. The research extends this by contending that the rational-sentiment axis as key variables responsible for market volatility maps into a price information vector.

Researchers	**Research title**	**Supporting evidence**
Kılıç and Uğur (2018)	Multiresolution analysis of S&P500 time series	Multiresolution analysis pinpoints special characteristics of stock market data, like periodicity as well as seasonality. For example, 'volatility clusters are basic indicators of financial [disasters]".
Stratimirović et al. (2018)	Analysis of cyclical behaviour in time series of stock market returns	"Given that financial markets are human-made complex systems, it is plausible to believe that […] findings can be explained by the fact that business cycles are a reflection of common human working habits and behaviour".
Mariani et al. (2020)	Analysis of stock market data by using Dynamic Fourier and Wavelets techniques	"The Fourier and Wavelet techniques are both efficient methodologies to detect a financial crash of the stock market".
Jun et al. (2019)	Signal analysis of global financial crises using Fourier series	"Fourier series can deduce financial information from the amplitude and phase of each component in the Fourier series".
Gallegati (2008)	Wavelet analysis of stock returns and aggregate economic activity	"Investors with longer term horizons are to be linked to macroeconomic fundamentals in their investment activity". "[Wavelets provide deeper understanding in] analysing the relationships that characterize markets where the agents involved consist of heterogeneous agents making decisions over different time horizons and/or operating at each moment on different time scales, as it is the case of financial markets".

4.2 The behavioural link between agents and markets

The research hypothesis proposes that 'rational and sentiment' is an information vector that drives upward and downward pressures in markets, and presented evidence supports this idea. This evidence presents the stock-price index as an equilibrium vector containing information structures made visible on a time plane by the wavelet transform. These information structures appear to depict the mind-set of the market as psychological aggregates of market agents along rational-sentiment lines. Translated differently and extending, the research hypothesis implies that price, in reflecting cost, balances agent psychological forces of value and worth, which enables an intuitive interpretation of the stock index trends using likelihood or beliefs. Belief in this context conveys a sense of psychological energy. This translation means that price in a market dimension reflects continuously changing nature of beliefs in the psychological dimensions of market agents. Thus, if the price of an asset as its worth to one market agent is equal the value in the cost to acquire it by another, price reflects costs and is the equilibrium of opposing rational and sentiment vectors from both agents.

In this sense, the market is then a platform interfacing price and cost forces. An alignment of price determinants in the psychological vectors of market agent creates a stable value (and worth) system, thus price is stable and it is reasonable to claim that rational (and sentiment) in the market is also stable (and gains are stable). Such an environment makes it possible to project market time trajectories. There are many scenarios to this however. Agent heterogeneity in terms of psychological directions and differences in environmental elements of markets increase likelihood for varying aggregates in market forces. Thus, generally and in the view of this study, changes in the market mind set can create sudden upward pressures (2008) or downward pressures (2012) on price structures that causes volatility. In 2008, a new price rational-sentiment vector emerges in the short-term horizons of the market, creating shocks on the volatility plane as seen from the FTSE 100 volatility index. In 2011-2012, the widely reported Greece debt crisis that affected bond yields in a similar manner brings forward a new cost mind set with downward pressures that coincides with an ending 7-8 market cycle, creating relatively smaller shocks on the volatility plane. The research's interpretive framework projects this by mapping the knowledge axis to the rational (sentiment) axis, making it possible to link agent psychology to market forces in time.

4.3 Conclusions

The London market seems to be perceptive. Davies and Studnicka (2018) discovers evidence of market intelligence illustrated by a relationship of FTSE stock returns to value chains of listed firms in Brexit periods. This is evidence of the capabilities around fundamental analysis investors have in efficient markets. This level of informational transparency as a key element of efficiency could explain the horizons of the 2008 market shocks in the London market compared to horizons in the Johannesburg market. It could also explain the change in market prices around 2012. From an efficiency point of view, a key challenge is comparing the Johannesburg market with the London market. A number of factors come into play here but the Johannesburg market does show resilience to change in a similar manner to the London market. This could give clues about the aggregate direction of the rational-sentiment vector in that market.

The story above is but an illustration of the capabilities of wavelet analysis in creating market narratives aided by complex analytics but are simple to understand. The insights from wavelet analysis images above in themselves might not be relevant, the key element is the meaning of information, its mapping to real world parameters and the transform techniques for projecting them.

5 DISCUSSION OF RESEARCH FINDINGS

Research findings are insights gained from re-examining questions guiding the exploration of literature. These research questions are important pathways in the knowledge field around the research question. Loosely bound, they mirror a similarly defined research question. This is a question of what information represents explored in this study by way of example using stock markets. Shedding light on the research question using the research hypothesis also sheds new light to the supporting questions. This light provides an opportunity to enhance understanding of the research field using a lens from this study.

The research questions are:

- What is a stock market as a system (looking at index construction and environment determinants of index trends, with focus on the JSE and LSE)?
- How can rational and sentiment help in explaining stock market behaviour?
- What is data and information in the context of stock markets and its connection to the market efficiency hypothesis?
- How can wavelet analysis reveal useful information describing psychological structures of stock markets and how can this explain JSE and LSE stock trends?
- How can evaluating the correlation of derived transformation elements with established market indicators validate this concept of market structural analysis?

From the discussion so far, the stock market appears to be a platform bounded by the width and length of time, where rational and sentiment vectors create an information pattern. The index represents the profile of this platform as a price information variable in the length of time. Assuming the index fairly represents the market; stock market behaviour then reflects elements of agents through a mapping of rational-sentiment to the index information. The term belief is an attempt to give a global instance of this behaviour, where belief is the strength of aggregate rational and sentiment directions in given market cycles. Data and information in the context of stock markets and its connection to market efficiency hypothesis is then its sufficiency in clearly mapping the market landscape.

Correlation analysis using the wavelet transform validates the concept of market structural analysis in enabling the localisation of market cycles effected by market bubbles. In different terms, the wavelet transform enables the analysis of market and volatility planes where cross wavelet compares is able to pinpoint their contact points. Correlation analysis of a market index and its volatility measure therefore creates possibilities of identifying market cycles affected by market bubbles or information spikes, as part of a search for market stabilization solutions. In this sense, cycles of time in the market seem to have an interesting meaning, a meaning that resonates with general concepts on oscillations. Because of this, it sounds reasonable to project rational and sentiment as some perpendicular waveforms in a frame of time as this sheds further light onto the meaning of the market price information vector. If the index share price is some price-weighted average of tradable stocks, then each moment on the index profile represents some market belief as some sum of rational and sentiment vectors. It should then follow that the source of the market index behaviour is rational and sentiment. Hence, investigating the behaviour of markets implies projecting the price index signal on a time plane and mapping each element in time to agent behaviour centred on time changing beliefs.

6 SUMMARY, CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS

6.1 Summary

The research problem is an analysis of market agents' behavioural patterns in the Johannesburg and London market index trends using information and liquidity as proxies. This problem definition gathers understanding of information by exploring its dimensions in ordinary stock market price data. The research hypothesis proposes that wavelet analysis resolves market price signals to fundamental forces whose patterns reveals the behaviour of market participants as belief patterns. An interpretive framework formulated around this claims that the market information axis links to the rational (sentiment) axis, however the exact mapping is undetermined. A key element of this mapping is that it seems to give structure to the market and human psychology link.

6.2 Conclusions

In a post-truth world, the definition of market efficiency based on information transparency risks its element of relevance. In this world, truth is an element of certainty and acceptance. Applied to markets, belief based on the likelihood of projected market outcomes becomes truth. If market efficiency is to consider meaning in information dimensions, understanding the axis of rationality-sentiment in information vectors might be key to establishing a clear relationship between markets and agent.

6.3 Limitations

Foreseeable research limitations are likely to be around the research instrument and research data. The tool applied in this study is a generic tool not specialised to processing the research data and this data is not specialised to the research question under examination. Because of these limitations, it is prudent to expect limited resolution of insights obtained from this study. The study however attempts to demonstrate pragmatism and its benefits on insights. In this, pragmatism ponders on how best to demonstrate that information is a vector.

6.4 Recommendations

The economic shutdown (CNN, BBC News and Xinhua net) taking place globally due to COVID-19 is exerting clear rational and emotional pressures on markets. Value chains are closing as the market re-evaluates worth, the economy or human life. This disruption of markets while catastrophic presents opportunities for further evaluating capabilities of insights derived from this study, a natural experiment for developing capabilities towards market engineering, market prediction and strategy formulation. In this sense, wavelet analysis of market signals in the times of the Corona virus outbreak can help identify affected market cycles to details dependent on the information efficiency of the given markets. In addition, like a whip crack sharper at its end, the market shock due the virus pandemic might behave differently to other shockwaves. Wavelet analysis can help analyse such suppositions by mapping the spread of shock waves across global markets due to the COVID-19 pandemic, with a benefit of understanding global market integration or synchronization. Thus, a key recommendation from this study is for corporates and investors to adopt deeper market structural analysis techniques such as the wavelet transform in order to remain competitive in this coming age of AI.

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Appendix 1.1: Research Data

Time	FTSE 100	FTSE All Share	FTSE 250	VIX	JSE Mining	JSE 40	JSE All Share
2004.08	4,390.68	2,187.10	6,023.90		14,311.28	9,953.72	10,849.25
2004.17	4,492.21	2,243.40	6,269.90		14,462.70	10,005.41	10,895.86
2004.25	4,385.67	2,197.00	6,259.40		13,545.34	9,773.27	10,692.56
2004.33	4,489.69	2,237.30	6,210.70		12,271.97	9,455.17	10,385.80
2004.42	4,430.69	2,201.80	6,053.60		12,365.28	9,525.95	10,413.81
2004.50	4,464.07	2,228.70	6,277.90		11,448.32	9,200.62	10,108.61
2004.58	4,413.08	2,192.22	6,023.50		11,937.25	9,405.23	10,305.89
2004.67	4,459.32	2,214.19	6,087.30	13.34	13,462.88	10,242.00	11,160.44
2004.75	4,570.77	2,271.67	6,269.10	12.45	13,994.45	10,780.46	11,761.00
2004.83	4,624.21	2,297.66	6,321.80	14.02	12,563.88	10,556.09	11,655.31
2004.92	4,703.18	2,345.21	6,577.40	12.64	12,888.62	11,283.33	12,490.79
2005.00	4,814.30	2,410.75	6,936.80	10.84	12,210.37	11,405.72	12,656.86
2005.08	4,852.31	2,441.22	7,166.20	10.84	12,815.77	11,530.91	12,798.55
2005.17	4,968.50	2,495.46	7,254.00	10.95	14,008.17	12,188.73	13,476.59
2005.25	4,894.37	2,457.73	7,130.50	10.72	14,024.10	12,083.30	13,298.60
2005.33	4,801.68	2,397.05	6,728.90	13.1	12,609.82	11,324.02	12,555.96
2005.42	4,963.97	2,483.35	7,114.30	10.84	14,671.40	12,518.60	13,787.00
2005.50	5,113.16	2,560.17	7,368.70	10.07	14,896.30	12,859.20	14,154.70
2005.58	5,282.30	2,644.75	7,605.10	10.59	15,537.20	13,725.80	15,143.60
2005.67	5,296.92	2,659.21	7,749.20	11.65	15,693.10	13,949.50	15,414.00
2005.75	5,477.71	2,745.79	7,951.10	10.27	18,180.80	15,363.60	16,875.70
2005.83	5,317.28	2,664.40	7,711.10	14.73	18,047.77	14,946.05	16,433.10
2005.92	5,423.17	2,741.05	8,327.90	12.26	18,638.23	15,228.83	16,774.54
2006.00	5,618.76	2,847.02	8,794.30	11.63	20,041.22	16,438.05	18,096.54
2006.08	5,760.26	2,928.56	9,172.60	12.77	22,498.11	17,886.18	19,745.16
2006.17	5,791.54	2,956.12	9,448.30	12.69	21,053.13	17,125.19	19,085.35
2006.25	5,964.57	3,047.96	9,850.30	12.44	22,716.25	18,314.78	20,351.74
2006.33	6,023.14	3,074.26	9,878.70	12.23	24,494.59	19,074.99	21,135.51
2006.42	5,723.81	2,916.85	9,298.20	21.27	25,053.85	18,660.12	20,565.46
2006.50	5,833.42	2,967.58	9,422.70	16.8	27,619.63	19,538.32	21,237.87
2006.58	5,928.33	3,004.28	9,355.60	16.48	26,450.09	19,127.38	20,885.57
2006.67	5,906.13	3,007.51	9,601.20	13.93	28,007.95	20,093.68	21,953.80
2006.75	5,960.81	3,050.44	9,996.80	14.2	27,877.50	20,495.74	22,374.58
2006.83	6,129.22	3,140.47	10,372.20	12.62	28,949.73	21,298.54	23,338.16
2006.92	6,048.85	3,119.85	10,673.90	13.52	29,322.70	21,758.65	23,949.95
2007.00	6,220.81	3,221.42	11,177.80	13.05	29,220.11	22,607.16	24,915.20
2007.08	6,203.09	3,211.84	11,100.30	14.36	29,641.75	22,941.71	25,447.73
2007.17	6,171.47	3,198.28	11,082.90	16.87	30,698.12	23,176.03	25,795.99
2007.25	6,308.03	3,283.21	11,689.30	14.89	33,959.54	24,590.20	27,267.24
2007.33	6,449.21	3,355.60	11,929.40	15.34	33,716.71	25,231.65	28,170.60
2007.42	6,621.45	3,438.70	12,111.10	14.28	35,990.59	25,701.40	28,627.79

2007.50	6,607.90	3,404.14	11,527.60	14.69	36,177.01	25,564.57	28,337.22
2007.58	6,360.11	3,289.12	11,337.50	21.8	36,576.48	25,846.41	28,561.81
2007.67	6,303.30	3,260.48	11,309.20	23.62	35,896.80	25,983.13	28,660.35
2007.75	6,466.79	3,316.89	11,037.40	20.65	40,651.86	27,267.58	29,959.19
2007.83	6,721.57	3,454.12	11,666.00	21.01	40,649.46	28,477.05	31,334.99
2007.92	6,432.45	3,280.87	10,748.80	23.74	39,234.13	27,629.35	30,307.80
2008.00	6,456.91	3,286.67	10,657.80	23.24	36,576.50	26,250.29	28,957.97
2008.08	5,879.78	3,000.10	9,881.80	29.03	37,701.16	25,117.79	27,317.14
2008.17	5,884.28	3,013.02	10,067.90	29.06	44,501.05	28,347.86	30,673.74
2008.25	5,702.11	2,927.05	10,013.20	26.09	42,732.75	27,409.99	29,587.51
2008.33	6,087.30	3,099.94	10,122.30	19.79	44,416.51	28,675.37	30,743.49
2008.42	6,053.50	3,082.26	10,049.30	21.25	47,180.95	29,939.96	31,841.27
2008.50	5,625.90	2,855.69	9,145.80	23.4	48,082.00	28,708.09	30,413.43
2008.58	5,411.90	2,749.21	8,856.70	21.79	38,555.26	25,779.21	27,719.67
2008.67	5,636.61	2,868.69	9,381.80	19.51	36,821.66	25,556.75	27,702.06
2008.75	4,902.45	2,483.67	7,888.20	39.68	28,167.06	21,746.97	23,835.97
2008.83	4,377.34	2,183.69	6,282.55	54.15	23,292.36	19,080.13	20,991.72
2008.92	4,288.01	2,133.99	6,093.32	44.65	24,751.10	19,346.28	21,209.49
2009.00	4,434.17	2,209.29	6,360.85	38.9	24,797.73	19,444.40	21,509.20
2009.08	4,149.64	2,078.92	6,250.76	41.76	24,089.83	18,519.77	20,570.05
2009.17	3,830.09	1,929.75	6,049.14	38.43	21,735.50	16,514.30	18,465.33
2009.25	3,926.14	1,984.17	6,373.89	36.4	25,061.39	18,441.62	20,363.91
2009.33	4,243.71	2,173.06	7,528.95	30.99	24,407.55	18,514.32	20,647.03
2009.42	4,417.94	2,252.64	7,572.00	26.83	28,396.76	20,605.38	22,770.62
2009.50	4,249.21	2,172.08	7,414.56	25.03	25,908.42	19,819.52	22,049.42
2009.58	4,608.36	2,353.47	7,999.96	23.77	28,714.27	21,855.80	24,258.51
2009.67	4,908.90	2,520.66	8,817.51	23.1	28,883.41	22,388.89	24,929.42
2009.75	5,133.90	2,634.79	9,142.31	22.35	28,817.31	22,284.39	24,910.85
2009.83	5,044.55	2,584.59	8,885.77	27.67	30,997.87	23,655.66	26,360.55
2009.92	5,190.68	2,648.43	8,918.44	25.82	33,157.01	24,357.77	26,894.74
2010.00	5,412.88	2,760.80	9,306.89	20.3	33,998.27	24,996.97	27,666.45
2010.08	5,188.52	2,660.49	9,237.30	22.9	31,696.75	24,041.26	26,675.95
2010.17	5,354.52	2,736.80	9,344.39	18.45	31,410.31	23,994.59	26,764.61
2010.25	5,679.64	2,910.19	10,165.28	16.76	34,506.33	25,833.44	28,747.56
2010.33	5,553.29	2,863.35	10,366.00	22.36	33,849.37	25,629.93	28,635.76
2010.42	5,188.43	2,673.17	9,637.14	25.95	31,676.19	24,157.99	27,145.36
2010.50	4,916.87	2,543.47	9,366.12	26.42	30,254.40	23,294.83	26,258.82
2010.58	5,258.02	2,715.36	9,948.72	22.08	32,082.32	25,224.60	28,355.21
2010.67	5,225.22	2,696.72	9,825.14	23.92	29,853.11	24,127.05	27,253.87
2010.75	5,548.62	2,867.58	10,531.80	20.78	31,805.10	26,154.31	29,456.04
2010.83	5,675.16	2,936.15	10,843.50	19.56	34,765.52	27,053.68	30,430.90
2010.92	5,528.27	2,861.61	10,607.75	24.61	34,625.60	26,844.52	30,266.40
2011.00	5,899.94	3,062.85	11,558.80	18.84	37,195.33	28,639.40	32,118.89
2011.08	5,862.94	3,044.27	11,471.51	18.99	36,988.99	28,145.34	31,398.75
2011.17	5,994.01	3,106.58	11,621.29	19.15	38,694.07	29,077.83	32,272.09
2011.25	5,908.76	3,067.73	11,591.98	16.42	37,361.76	29,037.48	32,204.06

2011.33	6,069.90	3,155.03	12,013.88	15.05	37,554.20	29,564.28	32,836.23
2011.42	5,989.99	3,121.07	12,060.79	16.09	36,579.94	29,274.06	32,565.73
2011.50	5,945.71	3,096.72	11,934.04	16.2	35,376.66	28,551.82	31,864.54
2011.58	5,815.19	3,026.02	11,552.06	19.16	33,859.97	27,857.91	31,208.04
2011.67	5,394.53	2,800.51	10,525.93	28.55	33,220.55	27,682.28	31,005.50
2011.75	5,128.48	2,654.38	9,819.38	37.76	31,244.47	26,375.82	29,674.20
2011.83	5,544.22	2,860.86	10,479.74	25.78	34,786.04	29,019.06	32,348.54
2011.92	5,505.42	2,835.84	10,315.29	25.45	35,155.28	29,429.88	32,812.64
2012.00	5,572.28	2,857.88	10,102.90	22.47	32,942.98	28,469.81	31,985.67
2012.08	5,681.61	2,932.91	10,769.35	20.15	35,885.23	30,176.19	33,792.48
2012.17	5,871.51	3,043.91	11,449.52	17.39	34,742.58	30,546.69	34,296.00
2012.25	5,768.45	3,002.78	11,538.88	17.19	31,500.40	29,603.42	33,554.21
2012.33	5,737.78	2,984.67	11,417.59	17.72	32,354.51	30,364.59	34,399.04
2012.42	5,320.86	2,767.09	10,558.22	26.88	29,864.50	29,201.90	33,142.61
2012.50	5,571.15	2,891.45	10,932.13	18.9	30,509.39	29,638.01	33,708.31
2012.58	5,635.28	2,927.27	11,136.69	18.16	29,842.95	30,386.61	34,596.90
2012.67	5,711.48	2,972.63	11,410.19	18.05	29,177.55	31,172.74	35,389.45
2012.75	5,742.07	2,998.86	11,734.10	15.31	30,686.84	31,518.32	35,757.98
2012.83	5,782.70	3,024.40	11,934.95	15.71	32,778.57	33,008.20	37,156.28
2012.92	5,866.82	3,065.30	12,034.22	12.16	32,001.07	33,872.69	38,104.61
2013.00	5,897.81	3,093.41	12,374.97	18.05	33,297.42	34,795.50	39,250.24
2013.08	6,276.88	3,287.38	13,030.49	13.32	34,217.26	36,103.45	40,482.92
2013.17	6,360.81	3,349.39	13,704.02	13.83	31,664.69	35,254.76	39,709.56
2013.25	6,411.74	3,380.64	13,923.04	12.33	29,929.39	35,259.10	39,860.84
2013.33	6,430.12	3,390.18	13,949.87	13.1	26,934.44	34,068.00	38,735.00
2013.42	6,583.09	3,473.82	14,350.92	15.85	29,963.23	37,599.86	42,016.45
2013.50	6,215.47	3,289.71	13,798.22	18.3	25,357.48	35,051.49	39,578.10
2013.58	6,621.06	3,509.94	14,872.86	16.59	27,896.25	36,843.05	41,292.84
2013.67	6,412.93	3,410.43	14,625.18	18.01	29,988.40	37,863.93	42,228.34
2013.75	6,462.22	3,443.85	14,908.18	15.36	30,384.92	39,449.84	44,031.83
2013.83	6,731.43	3,585.32	15,479.95	12.81	30,764.36	40,658.55	45,517.56
2013.92	6,650.57	3,548.45	15,466.56	11.95	30,046.08	40,169.32	44,975.67
2014.00	6,749.09	3,609.63	15,935.35	12.26	30,511.79	41,482.39	46,256.23
2014.08	6,510.44	3,496.51	15,674.37	18.23	32,471.78	40,586.73	45,132.10
2014.17	6,809.70	3,666.66	16,726.00	13.07	34,058.38	42,771.61	47,328.92
2014.25	6,598.37	3,555.59	16,273.72	13.04	32,925.71	42,996.63	47,770.92
2014.33	6,780.03	3,619.83	15,817.20	11.85	34,414.90	43,804.68	48,870.10
2014.42	6,844.51	3,655.01	16,010.25	11.42	32,528.24	44,641.55	49,632.70
2014.50	6,743.94	3,600.19	15,723.56	11.27	33,431.72	45,969.81	50,945.26
2014.58	6,730.11	3,585.62	15,495.64	13.87	35,589.01	46,222.43	51,396.07
2014.67	6,819.75	3,639.54	15,885.72	11.3	33,113.94	45,630.44	50,959.02
2014.75	6,622.72	3,533.93	15,379.72	13.87	30,248.60	44,160.31	49,336.31
2014.83	6,546.47	3,503.46	15,501.37	14.16	27,130.06	44,384.99	49,722.88
2014.92	6,722.62	3,593.32	15,851.76	10.9	26,200.71	44,205.76	49,911.37
2015.00	6,566.09	3,532.74	16,085.44	17.96	25,100.95	43,969.96	49,770.60
2015.08	6,749.40	3,621.81	16,305.77	16.44	25,588.75	45,111.03	51,266.81

2015.17	6,946.66	3,744.26	17,273.82	11.87	28,167.44	47,161.83	53,344.20
2015.25	6,773.04	3,663.58	17,090.64	16.33	24,769.28	46,016.98	52,181.95
2015.33	6,960.63	3,760.06	17,474.63	17.67	26,733.07	48,195.48	54,440.43
2015.42	6,984.43	3,797.12	18,154.42	13.81	25,344.93	46,285.65	52,270.86
2015.50	6,520.98	3,570.58	17,531.50	19.05	23,544.98	46,141.59	51,806.95
2015.58	6,696.28	3,652.79	17,677.40	13.61	21,548.48	46,557.26	52,053.27
2015.67	6,247.94	3,434.66	17,106.36	24.26	21,336.99	44,350.11	49,972.33
2015.75	6,061.61	3,335.92	16,683.02	24.14	18,777.84	44,881.18	50,088.86
2015.83	6,361.09	3,484.60	17,117.21	14.93	19,890.81	48,317.45	53,793.74
2015.92	6,356.09	3,492.13	17,420.70	16.95	15,779.59	46,329.56	51,607.83
2016.00	6,242.32	3,444.26	17,429.82	17.45	15,260.58	45,797.30	50,693.76
2016.08	6,083.79	3,335.90	16,487.72	21.87	15,098.53	44,065.55	49,141.94
2016.17	6,097.09	3,345.84	16,603.08	22.06	18,691.94	43,802.56	49,415.31
2016.25	6,174.90	3,395.19	16,926.12	16.5	19,770.38	46,139.99	52,250.28
2016.33	6,241.89	3,421.70	16,801.55	16.74	23,505.12	46,471.00	52,957.32
2016.42	6,230.79	3,429.77	17,184.73	17.41	21,527.04	47,974.09	53,905.21
2016.50	6,504.33	3,515.45	16,271.07	19.89	22,289.91	45,974.31	52,217.72
2016.58	6,724.43	3,653.83	17,282.88	12.94	23,800.91	45,916.48	52,797.58
2016.67	6,781.51	3,697.19	17,732.77	13.36	23,076.25	46,261.02	52,733.12
2016.75	6,899.33	3,755.34	17,871.42	14.2	24,474.10	45,425.59	51,949.83
2016.83	6,954.22	3,768.14	17,544.24	16.03	23,516.65	44,019.39	50,590.08
2016.92	6,783.79	3,692.40	17,545.75	15.95	25,121.48	43,691.42	50,209.43
2017.00	7,142.83	3,873.22	18,077.27	11.56	23,510.63	43,901.99	50,653.54
2017.08	7,099.15	3,858.26	18,147.77	12.95	26,917.80	45,928.70	52,788.12
2017.17	7,263.44	3,953.42	18,770.71	11.11	23,506.22	44,131.37	51,146.05
2017.25	7,322.92	3,990.00	18,971.83	11.81	23,556.97	45,167.15	52,056.06
2017.33	7,203.94	3,962.49	19,615.36	11.17	22,865.22	47,071.73	53,817.31
2017.42	7,519.95	4,116.08	19,972.17	11.67	21,800.92	47,153.91	53,562.57
2017.50	7,312.72	4,002.18	19,340.15	13.03	21,339.17	45,421.76	51,611.01
2017.58	7,372.00	4,046.20	19,781.14	10.82	25,160.93	48,873.13	55,207.41
2017.67	7,430.62	4,072.98	19,803.59	11.64	26,713.58	49,997.27	56,522.11
2017.75	7,372.76	4,049.89	19,874.82	10.43	25,981.86	49,376.46	55,579.92
2017.83	7,493.08	4,117.69	20,227.86	9.82	28,171.43	52,570.20	58,980.11
2017.92	7,326.67	4,033.84	19,952.89	10.84	27,411.77	53,269.83	59,772.83
2018.00	7,687.77	4,221.82	20,726.26	9.55	27,351.42	52,533.04	59,504.67
2018.08	7,533.55	4,137.66	20,243.60	12.53	28,712.09	52,614.65	59,506.12
2018.17	7,231.91	3,981.61	19,687.27	14.08	27,062.49	51,383.45	58,325.09
2018.25	7,056.61	3,894.17	19,460.47	13.75	25,747.71	48,794.50	55,474.52
2018.33	7,509.30	4,127.68	20,285.05	11.68	27,923.80	51,419.22	58,252.12
2018.42	7,678.20	4,222.20	20,846.26	13.53	29,052.55	49,783.92	56,157.89
2018.50	7,636.93	4,202.25	20,830.97	13.71	30,561.08	51,516.06	57,610.98
2018.58	7,748.76	4,253.31	20,877.87	11.64	29,826.59	51,315.00	57,432.46
2018.67	7,432.42	4,106.14	20,689.00	12.92	30,580.35	52,464.01	58,668.48
2018.75	7,510.20	4,127.91	20,307.04	11.75	31,162.27	49,520.66	55,708.47
2018.83	7,128.10	3,904.23	18,917.68	16.84	30,842.40	46,141.22	52,388.87
2018.92	6,980.24	3,823.34	18,480.83	17.86	27,660.21	44,656.89	50,663.94

2019.00	6,728.13	3,675.06	17,502.05	22.09	32,057.48	46,726.59	52,736.86
2019.08	6,968.85	3,825.62	18,711.75	13.93	33,555.81	47,955.98	54,156.75
2019.17	7,074.73	3,888.81	19,181.35	13.49	37,294.06	49,667.10	56,002.08
2019.25	7,279.19	3,978.28	19,117.49	12.85	38,719.10	50,273.93	56,462.55
2019.33	7,418.22	4,067.98	19,824.81	11.64	37,210.65	52,274.03	58,528.40
2019.42	7,161.71	3,923.87	18,970.25	13.55	36,588.12	49,587.47	55,650.41
2019.50	7,425.63	4,056.88	19,462.10	11.03	41,339.99	52,198.94	58,203.84
2019.58	7,586.78	4,134.03	19,666.52		39,334.03	50,798.70	56,784.61
2019.67	7,207.18	3,953.02	19,393.63		39,636.63	49,320.23	55,259.57
2019.75	7,408.21	4,061.74	19,936.67		39,108.82	48,813.59	54,824.97
2019.83	7,248.38	3,993.46	20,021.50		41,954.86	50,168.48	56,425.11
2019.92	7,346.53	4,066.73	20,812.60		41,497.90	49,093.16	55,349.01
2020.00	7,542.44	4,196.47	21,883.42		44,273.88	50,816.05	57,084.10
2020.08	7,286.01	4,057.47	21,143.49		43,698.60	50,072.61	56,079.54
2020.17	6,580.61	3,673.61	19,330.92		38,635.48	45,851.76	51,038.18
2020.25	6,790.95	3,707.32	19,923.15		40,980.84	46,648.20	51,840.09

Appendix 2.1: Data analysis program

```
%% Computation of wavelet power using AWT
%{(AWT - Analytic Wavelet Transform) Generates a picture similar to that of Example
1: Motivation in Aguiar-Conraria, L. and Soares, M.J. (2014) "The continuous wavelet
transform: moving beyond the
   uni- and bivariate analyis", Journal of Economic Surveys, 28(2), 344-375 DOI:
10.1111/joes.12012
 NOTE: There are differences because here we use normalized power, instead of power,
and we also plot the levels of significance
%}
% ----- Clear all variables and screen  -------------
clear;
clc;
rng default
%-----------    Update  path  -------------------------
%
%-------------------------------------------------------
%Path for loading the wavelet functions (has to be changed)
addpath('Functions/Auxiliary');
addpath('Functions/WaveletTransforms');
%
names = cell(1,1);
names{1} = 'Index Name';
% -----------     Generation of series x   --------------------------------

% Read data
d = xlsread('Research data');
d = d(:,1:3); % Time and index matrix
% -------------     Choice of wavelet transform parameters   -----------------------
dt = 1/2;
dj = 1/30;
low_period = 1;
up_period = 18;
% --------------------- Choice of boundary conditions        -----------------------
pad = 1;     % 1 or 'reflexive' -> reflection at the boundaries

%----------------------- Choice of wavelet -----------------------------
mother = 'Morlet'; % Morlet wavelet
beta = 6.0; % omega parameter for the Morlet
gamma = 0;  %
%-------------- Choice of method to compute significance levels -----------
sig_type = 'MCS'; % 3 or 'MCS'->  Monte Carlo simulation
n_sur = 5000;
p = 1;
q = 1;
% ************       MAIN COMPUTATIONS *******************
%-----  Wavelet Power and corresponding p-values --------
x = d(:,1+2); % FTSE 100 (1+1), VIX (1+2)

[~,periods,coi,power,pv_power] =...
    AWT(x,dt,dj,low_period,up_period,pad,mother,beta,gamma,sig_type,n_sur,p,q);

%-------   Local maxima of WPS (ridges)  -----------
max_power = MatrixMax(power,3,.2);

%-----  Global wavelet power apectrum (GWPS) ---------
GWPS = mean(power,2);

% *********************       PLOTS   *************************************
fig1 = figure(1);
%---  Plot of Series ----
plotSeries = subplot(3,2,[1 2]);
    % Time
    t = d(:,1);
    x_lim = [t(1) t(end)+dt];
    x_ticks = 2004:2:2020;

    y_lim = [8,55];
    y_ticks = 8:5:55;

    plot(t,x,'b-','LineWidth',0.75);
    set(plotSeries,'XLim',x_lim,'XTick',x_ticks,'XTickLabel',x_ticks);
```

```
    set(plotSeries,'Ylim',y_lim,'YTick',y_ticks,'YTickLabel',y_ticks);
    set(plotSeries,'FontName','arial','FontSize',6);
    grid on
    title('   VIX Index - Wavelet Analysis',...
         'FontSize',11)
% ---   Plot of wavelet power  ------
% (and  COI, ridges and levels of significance)
logcoi=log2(coi);
logperiods = log2(periods);
y_lim_power = [min(logperiods) max(logperiods)] ;
y_ticks_power_lab = [1 3  5 10];
y_ticks_power = log2(y_ticks_power_lab);
perc5 = 0.05; % To plot 5% levels of significance
% ------ WPS ----------------
pic_enh = 0.5; % Picture enhancer
plotPower = subplot(3,2,[3 4]);
    imagesc(t,logperiods,power.^pic_enh)
    colormap(jet); % So that colors are as in older Matlab version
    set(plotPower,'XLim',x_lim,'XTick',x_ticks);
    set(plotPower,'YLim',y_lim_power,'YTick',y_ticks_power, ...
       'YTickLabel',y_ticks_power_lab, 'YDir','reverse');
    set(plotPower,'FontSize',6,'FontName','arial');
    xlabel('Time')
    ylabel('Period');
    grid on
    title('    Wavelet Power Spectrum','FontSize',7)
    hold on
    % COI
    plot(t,logcoi,'k','LineWidth',1.5);

    % Ridges
    caxis('manual')
    contour(t,logperiods,max_power,[1,1],'w-','LineWidth',1.25);
    [cc,hh] = contour(t,logperiods,pv_power,[perc5,perc5],...
                       'Color','k','LineWidth',1.25);
     set(hh,'ShowText','on');
   hold off


%---- Global wavelet power spectrum ----
plotGWPS = subplot(3,2,5);
    plot(GWPS,logperiods,'LineWidth',1)
     set(plotGWPS,'YTick',y_ticks_power,'YTickLabel',y_ticks_power_lab,...
        'YDir','reverse')
    set(plotGWPS,'FontName','arial','FontSize',6)
    title('    GWPS','FontSize',7)
    ylabel('Period')

% **** Computation and plot of Fourier Power Spectrum ***
%      (Uses function FourierSpectrum in folder Auxiliary)
plotFPS = subplot(3,2,6);
    min_period = 1;
    max_period = 16;
    spP = FourierSpectrum(x,40,0,2,dt,min_period,max_period);

    xlabel('Period')
    xticks=[1 3 5 10];
    set(plotFPS,'XTick',xticks,'XTickLabel',xticks);
    set(plotFPS,'FontName','arial','FontSize',6)
    title('   Power Spectral Density','FontSize',7)
    %set(fig1,'NumberTitle','off','Name','Fig_Example1')
% ******************* Save figure *********************************
set(fig1, 'PaperPositionMode', 'manual');
set(fig1, 'PaperUnits', 'centimeters');
set(fig1, 'PaperPosition', [2 2 12 10]);
print('Fig_Power_Spectrum_Image,'-r600','-dpng');



%% Computation of coherency using AWCOG
%{(AWCOG - Analytic Wavelet Coherency and Gain)
Generates a picture similar to that of Example 2: The Cross-Wavelet and the Phase-
Difference in Aguiar-Conraria, L. and Soares, M.J. (2014) "The continuous wavelet
transform: moving beyond the uni- and bivariate analyis", Journal of Economic
Surveys, 28(2), 344-375 DOI: 10.1111/joes.12012
 NOTE: Pictures are different due to random error and a different way to compute
phase-differences; also, here we plot phase-differences (and not time-lags)
```

```
%}

%-------- Clear all variables and screen ------------
clear;
clc;
rng default
%--------------------------- Path update --------------------------------
%Path for loading the wavelet functions (has to be changed)
addpath('Functions/Auxiliary');
addpath('Functions/WaveletTransforms');

% ------------------   Generation of series x and y     ----------------
% Read data
d = xlsread('Research data');
d = d(:,1:3); % Time and index data

 t = d(:,1);
 y = d(:,1+1); %Index 1
 z = d(:,1+2); %Index 2

% ----------     Choice of parameters for the wavelet transforms -----------
dt = 1/2;
dj = 1/60;
low_period = 1;
up_period = 18;
% -------------------- Choice of boundary conditions        ---------------
pad = 1;     % 1 or 'reflexive' -> reflection at the boundaries
%------------------------ Choice of wavelet --------------------------------
mother = 'Morlet'; % Morlet wavelet
beta = 6.0; % omega parameter for the Morlet
gamma = [];  % Not important, because mother wavelet is the Morlet
% --- Choice of size of windows for smoothing in coherency computation ----
wt_size = 2; % Actual size used varies with scale s and
%              is given by:  wt_size*s/dt (with a minimum value of 5)
ws_size = 2; % Actual size used depends on dj and is
%              given by: ws_size/(2*dj) (with a minimum value of 5)

%-------------------------------------------------------------------------
%  Number of surrogates for computing significance levels
n_sur = 1000; % TAKES LONG!
% (Use a smaller number just to test)
% Choice of parameters p and q for ARMA model of series
 p = 1;
 q = 1;
%--------------------------------------------------------------------------
%******************        MAIN COMPUTATIONS        ***************

% Wavelet Coherency and p_values

[WCO,Wxy,periods,coi,pv_WCO] = AWCOG(y,z,dt,dj,low_period,up_period,pad,mother,...
                               beta,gamma,wt_size,ws_size,n_sur,p,q);
%
% WT of y
waveY = AWT(y,dt,dj,low_period,up_period,pad,mother,beta,gamma);

% WT of Z       ***********************+
waveZ = AWT(z,dt,dj,low_period,up_period,pad,mother,beta,gamma);

% ----------  Choice of  (period) band selections    -------------------
%          for phase and phase-difference computations
lowF1 = 2.5;
upF1 = 3.5;

lowF2 = 5;
upF2 = 7;
% ------ Computation of phases for Y   ------
phaseXF1 = MeanPHASE(waveY,periods,lowF1,upF1);

phaseXF2= MeanPHASE(waveY,periods,lowF2,upF2);

%------   Computation of phases for z  ------
phaseYF1 = MeanPHASE(waveZ,periods,lowF1,upF1);

phaseYF2 = MeanPHASE(waveZ,periods,lowF2,upF2);

% -------        Computation of phase-differences  ----------
%                    (using coherency)
```

```
phaseDifF1 = MeanPHASE(WCO,periods,lowF1,upF1);

phaseDifF2 = MeanPHASE(WCO,periods,lowF2,upF2);
% ******************* PLOTS ********************************
fig2 = figure(2);
x_lim = [t(1) t(end)];
x_ticks = 2004:2:2020;


logcoi = log2(coi);
logperiods = log2(periods);
y_limCO = [min(logperiods), max(logperiods)];
y_ticksCO_lab = [1 3 6 9];
y_ticksCO = log2(y_ticksCO_lab);

y_limPhase = [-pi-0.1 pi+0.1];
y_ticksPhase = -pi: pi/2 : pi;
y_ticksPhase_lab = {'-\pi','-\pi/2','0','\pi/2','\pi'};


% --------- Plot of series -------------
plotSeries=subplot(3,2,[1 2]);

    z_n = 142*z;
    plot(t,y,'b',t,z_n,'r');
    hold on

    grid off
    set(gca,'YTick',[])

    tit='  Series: FTSE 100 and VIX Indexes';
    set(plotSeries,'XLim',x_lim,'XTick',x_ticks,'XTickLabel',x_ticks);
    set(plotSeries,'FontName','arial','FontSize',6);
    title(tit,'FontName','arial','FontSize',11);
    hold off

% ---------- Plot of coherency, COI and levels of significance ------------
plotWCO = subplot(3,2,[3 4]);
    pictEnh = 5; % Picture enhancer
    % Coherency
    imagesc(t,logperiods, abs(WCO).^pictEnh);
    colormap(jet)
    caxis('manual')
    ylabel('Period');
    xlabel('Time');
    set(plotWCO,'XLim',x_lim);
    set(plotWCO,'YLim',y_limCO,'YTick',y_ticksCO,'YTickLabel',y_ticksCO_lab,...
        'YDir','reverse')
    set(plotWCO,'FontName','arial','FontSize',6);
    title('  Wavelet Coherency','FontName','arial','FontSize',7);
    grid on
    hold on
    % COI
    plot(t,logcoi,'k','LineWidth',2);

    % Levels of significance
    [cc,hh] = contour(t,logperiods,pv_WCO,[0.05,0.05],...
                       'Color','k','LineWidth',1.25);
     set(hh,'ShowText','on');
     hold off
%---------------   Plot of Phases and Phase-Differences ------------

plotPhaseDif1 = subplot(3,2,5);
    plot(t,phaseXF1,t,phaseYF1);
    hold on
    plot(t,phaseDifF1,'LineWidth',1.5,'Color','r');
    xlabel('Time');
    set(plotPhaseDif1,'XLim',x_lim,'XTick',x_ticks)
    set(plotPhaseDif1,'YGrid','on','YLim',y_limPhase,'YTick',y_ticksPhase,...
        'YTickLabel',y_ticksPhase_lab)
    set(plotPhaseDif1,'FontName','arial','FontSize',6)
    title({'    Phase-Differences' '2.5~3.5 frequency band'},...
          'FontName','arial','FontSize',7);
  hold off
%
plotPhaseDif2 = subplot(3,2,6);
    plot(t,phaseXF2,t,phaseYF2);
```

```
    hold on
    plot(t,phaseDifF2,'LineWidth',1.5,'Color','r');

    xlabel('Time');
    set(plotPhaseDif2,'XLim',x_lim,'XTick',x_ticks)
    set(plotPhaseDif2,'YGrid','on','YLim',y_limPhase,'YTick',y_ticksPhase,...
        'YTickLabel',y_ticksPhase_lab)
    set(plotPhaseDif2,'FontName','arial','FontSize',6)
    title('5~7 frequency band','FontName','arial','FontSize',7);
  hold off
 % Save figure
set(fig2,'NumberTitle','off','Name','Fig_Example2')
set(fig2, 'PaperPositionMode', 'manual');
set(fig2, 'PaperUnits', 'centimeters');
set(fig2, 'PaperPosition', [2 2 14 12]);
print('Fig_Coherency_image','-r600','-dpng')
```

Appendix 2.2: Ethic documentation

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/BA1838703/146

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (bel

This certificate is only valid if accompanied by formal permission from the relevant stakeholder(s).

Project title	Wavelet analysis of Stock Market trends: Investigating behavioural patterns in the Johannesburg and London Stock Markets
Investigator / Researcher	Mr Ronald Mwenye
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved unconditionally
Issue Date of Certificate	2/12/2020
Expiry date	Date of submission of the project report
Chairperson	Prof Anthony Stacey ☎ +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

2/12/2020
Date: