LIQUIDITY SHOCKS AND CAPITAL MARKET EFFICIENCY IN SOUTH AFRICA

Dexter Tinotenda Kushinga Matapuri

G17M1456

Department of Economics and Economics History

Rhodes University

Thesis submitted in partial fulfilment of the requirement for the degree of

MASTER OF COMMERCE (FINANCIAL MARKETS)

(Half thesis)

Supervisors: Prof. H. Nel & Dr S.A. Khumalo

October 2023.

ACKNOWLEDGMENTS

I would like to firstly thank the Lord Almighty for giving me the strength to see this thesis through. My deepest gratitude goes to my supervisors, Prof Nel and Dr Khumalo for taking me under their wings and sharing their archives of knowledge. I would also like to thank the Rhodes University Economics Department for growing me as a person through academic and social engagements.

To my parents, Dadirai and Ellison Matapuri, whom I could not have taken this journey without, I shall forever be grateful. Special thanks go to my brothers Denzel and Divine Matapuri and the friends who kept me in touch with my inner self throughout my academic career.

ABSTRACT

Financial markets are dynamic in nature. As such, one way to keep up with their plethora of variables is to conduct research and seek understanding on how they all work together. Understanding financial market mechanics is the key to achieving and maintaining efficient capital markets. The goal of many economies is to have efficient capital markets mainly because they entail economic growth. One of the common avenues here being foreign direct investments. Therefore, over the years, a lot of financial economics research has been conducted on how best to attain financial market development which ultimately yields capital market efficiency. The opposite is also true.

This research therefore set out to study the impact of liquidity shocks on capital market efficiency, more specifically stock market efficiency. As such, the overarching research goal was to determine the link between liquidity shocks and stock market efficiency in South Africa. Furthermore, the research also tested whether there is a homogenous impact exerted by liquidity shocks on the JSE Financial 15, JSE Industrial 25 and JSE Resource 20 indices. The arguments and thus conclusions of the research were constructed based on existing theories such as the Efficient Market hypothesis, Behavioural Finance and the Adaptive Market Hypothesis. Literature and existing empirical evidence related to the topic were also analysed and used for the same purpose. Econometric methods used to achieve these research goals include the time series and panel ARDL, impulse response and variance decomposition tests and the Granger Causality tests.

The research found that liquidity shocks do impact stock market efficiency in South Africa in both the short run and long run. The direction of the impact was noted to vary with time and dependent on the liquidity shock proxy. Key findings here were that liquidity shocks lower JSE All-Share index efficiency in the short run thus allowing market participants to beat the market in the initial phases of a liquidity shock. Adding on, it was also found that illiquidity shocks lower efficiency for the JSE Financial 15 and Industrial 25 indices in the short run. In the long run, stock market efficiency is enhanced no matter the source of the shock. As such, the research recommended that regulatory policies should focus on liquidity shocks in the short run for the JSE All-Share index and on illiquidity shocks in the short run for the Financial 15 and Industrial 25 indices.

TABLE OF CONTENTS

LIST OF TABLES.

LIST OF FIGURES

LIST OF ACRONYMS

ADF	Augmented Dicky Fuller.
AMH	Adaptive Market Hypothesis.
ARCH	Autoregressive Conditional Heteroskedastic.
ARDL	Autoregressive Distributed Lag.
ARI	Arrowhead Renewal Improvements.
ARMA	Autoregressive Moving Average.
BF	Behavioural Finance.
BSE	Bombay Stock Exchange.
CAPM	Capital Asset Pricing Model.
CRS	Chordia Roll and Subramanyam (2008).
DFA	Detrended Fluctuation Analysis.
DSE	Dhaka Stock Exchange.
ECT	Error Correction Term.
EMH	Efficient Market Hypothesis
FDI	Foreign Direct Investment.
FMD	Financial Market Development.
GARCH	Generalised Autoregressive Conditional Heteroskedastic.
IR	Idiosyncratic Risk
IRF	Impulse Response Function.
IV	Idiosyncratic Volatility

JSE	Johannesburg Stock Exchange
JSE	Jamaican Stock Exchange
KSE	Karachi Stock Exchange
LSE	London Stock Exchange.
NSE	Nairobi Stock Exchange.
NYSE	New York Stock Exchange.
PP	Phillips Perron.
PMG	Pooled Mean Group
SME	Stock Market Efficiency.
VAR	Vector Autoregressive
VECM	Vector Error Correction Model.

CHAPTER 1

OVERVIEW OF THE STUDY

1.1 Introduction and Background of the research.

The importance of financial markets is reflected in their ability to allocate funds efficiently and thus facilitate sustainable economic growth (Bekaert and Harvey, 1998). This entails creating channels for funds to flow from surplus units to deficit units. A category of the financial market system that enhances this function is capital markets. Bekaert, Garcia, and Harvey (1995) showed that efficient capital markets ensure investors access to fair prices for their securities which boosts investment and economic activity. As such many researchers have confirmed that the continuous advancement of capital markets has positively contributed to economic growth. Spearheading the research on capital markets and economic growth, Levine and Zervos (1996) showed by using cross-country growth regressions that long-run economic growth was robustly linked to stock market development. In agreement with the latter, Brasoveanu *et al* (2008) confirmed these findings in Romania where their results showed that capital market development shares a positive correlation with economic growth. Kolapo and Adaramola (2012) conduct a similar study on the Nigerian capital markets and also find a positive impact on economic growth from capital markets.

Notice that capital market development contributes to overall financial market development (FMD) since as mentioned above, capital markets fall under financial markets and thus the financial system as a whole. According to the World Bank (2016), the crux of financial market development is minimising costs thus reducing frictions incurred by participants operating in the financial system. As such, one can therefore denote that financial market development occurs when all facets responsible for the key functions of the financial sector such as instruments, markets and intermediaries collectively ease the effects of transaction costs, information, and enforcement (World Bank, 2016). Adding on, given the vastness of FMD as a concept, it is no surprise that it can prove difficult to measure. However, the World Bank

(2016) classified FMD under the following categories: stability, financial depth, ***efficiency***, and access. This research focuses on efficiency as a measure since it focuses more on the price impact and wealth accumulation (World Bank, 2016).

The importance of FMD is further shown in recent literature which reveals its significance in creating prime conditions for foreign direct investment (FDI) that also contributes to economic growth. According to Otchere, Soumare and Youeougou (2016), well-functioning financial markets play a significant role in channelling foreign investments efficiently into the host country's productive sectors. The end result being additional value for investors, making the host country even more attractive for further FDI. Donaubauer, Neumayer and Nunnenkamp (2020), add onto this argument and note that FMD in both the host and source country is important for a bilateral increase in FDI. For capital markets in the host country, another benefit is the listing of companies from the source country involved in FDI, which positively adds to the market capitalisation (Otchere, Soumare and Youeougou, 2016).

The research makes use of the link between liquidity and capital market efficiency which ultimately affects financial market development as explained by the World Bank (2016). According to Rosch (2015), arbitrageurs induce liquidity which in turn improves market efficiency. However, Tetlock (2007) critics this position with the idea that liquidity actually represents noise trading and thus negatively affects market efficiency. To gain a better understanding of these arguments, let's start by defining the liquidity concept and its effects on the financial system. Santoso *et al* (2010) states that asset liquidity is the capability of a financial asset to be sold or bought at a stable price, without losing value. More specifically, Crocket (2008) notes that a liquid asset would exhibit low transaction costs, allows quick settlement, and be traded in large volumes without drastically changing the market price of the financial asset. This definition includes the four most important aspects of asset liquidity namely depth, tightness, immediacy, and resilience (Santoso *et al*, 2010). Another important aspect of liquidity brought forward by Amihud (2002) is liquidity shocks. The latter describes liquidity shocks as unforeseen changes in the demand for liquidity. Adding on Bali *et al* (2014) highlighted that further studies on liquidity shocks could enhance our understanding of how the market processes such shocks, thus adding insight on the informational efficiency of financial markets.

Since this research aims to look at the liquidity and efficiency of the Johannesburg Stock Exchange (JSE), here are some highlights to be further explored in the coming chapters on these aspects. Heymans and Santana (2018) conducted a study to evaluate the efficiency of the JSE and found that portfolio managers have a tendency to hold smaller stocks that are illiquid and somewhat informationally inefficient thus allowing them to beat the market and earn abnormal returns. Overall, the latter concluded that the JSE was weak form efficient although it goes through periods of inefficiency. Fusthane and Kapingura (2017) echoe these findings but add that further steps needed to be taken to enhance the efficiency of the JSE especially in times of financial shocks. Adding on, a look at the recent literature points to the fact that the JSE stocks go through ebbs and flows. Kunjal (2021) looked at the behaviour of liquidity during the COVID 19 pandemic. Here the findings pointed at liquidity drying up on the JSE especially during the hard lock down (March 2020 to June 2020). Here it was also noted that the liquidity of stocks on the JSE is not consistent over time as also seen with efficiency. Notice therefore that both variables for this research are dynamic nature.

1.2 Problem Statement.

The recent international financial crisis (2007-2008) has drawn much needed focus on liquidity and the effects of liquidity shocks on financial markets. Bali *et al* (2014) note that there already exists a positive relationship between stock illiquidity and expected returns. This is mainly due to the illiquidity premium demanded by investors (Amihud and Mendelson, 1986). From this understanding, Bali *et al* (2014), point out that negative liquidity shocks give way to future lower liquidity thus even higher expected returns. Many researchers have, however, contested how well the latter relationship would hold in a market with poor information symmetry. It is known that when information is not adequately reflected onto asset prices, the extent of market efficiency comes into question. As such, the relationship between liquidity shocks and expected returns becomes blurry when we consider the level of efficiency within a particular market.

Furthermore, a fundamental concern raised by the World Bank Group (2020) is that developing economies underutilize domestic capital markets and thus only yield a small portion of their benefits. Additionally, the agency to develop financial markets and hence achieve efficiency is enhanced by the increased number of delisting's on the Johannesburg Stock Exchange (Buthelezi, 2022). More so, although South African financial markets are more advanced as compared to other developing economies (Yartey, 2008), there is still a need to conduct research and bridge the gap between liquidity shocks and their effects on market efficiency and ultimately financial market development. This is a step towards ensuring that South Africa does not underutilise the domestic capital market and miss out on the aforementioned benefits.

1.3 Rationale, Significance and Contribution of the study.

The background section has shown the importance of efficient markets and how they contribute to overall financial market development and even economic growth (Levine and Zervos, 1996). The rationale of this research is thus to understand the mechanics of stock market efficiency in relation to liquidity shocks. As mentioned in the previous section there exists a gap in literature for the relationship between liquidity shocks and stock market efficiency. Therefore, findings from the research will assist regulators to understand how best to improve the efficiency of the JSE and thus bring it closer to world standards. This research can also offer insight to portfolio managers and other stock market participants on how liquidity shocks strengthen or weaken efficiency. Such knowledge could help the latter parties to formulate strategies on how best to maximise their returns.

1.4 Goals of the Research.

The overarching goal of the research is to investigate how liquidity shocks impact capital market efficiency in South Africa. The sub-goals are therefore to.

1.4.1 Determine how liquidity shocks as measured by the change in turnover ratio and the Amihud illiquidity-measure impact capital market efficiency in South Africa.

1.4.2 Determine if the relationship between liquidity shocks and capital market efficiency is homogenous across the three sectors investigated namely the resource, industrial and financial sectors of the JSE.

1.5 Methods, Procedures, Techniques and Ethical Considerations.

The research will make use of daily stock data for a period of ten years (01/01/2012-01/01/2022) which will be acquired from the Johannesburg Stock Exchange using IRESS and Thomson Reuters DataStream. The FTSE/JSE All-share index will be used to proxy the entire

South African capital market. Three sectors namely the resource, industrial and financial sector will also be utilised to complete the hypothesis explained below. Operating under the post-positivist paradigm, the study employs a similar model as Gunawan and Hendrawaty (2018) by using this data to compute stock market liquidity values involving the measures explained below. Note here that capital market efficiency will be proxied by the stock market turnover ratio (stocks traded to market capitalisation) (World Bank, 2016). A cointegration panel and time series study which will use the Autoregressive Distributed Lag (ARDL) estimation model is employed. The panel results will further be used to test the hypothesis that there is no variation in the impact of liquidity shocks on capital market efficiency across the three sectors highlighted above.

Additionally, the research will make use of two liquidity measures, the stock market turnover and the Amihud illiquidity measure. The stock market turnover measure is an outright and simple method which indicates how much quantity investors trade at a point in time divided by the market capitalisation. It is an indication of the depth of the market (Narasimhan and Kalra, 2014). Another study covered by the research in the literature and empirical findings due to its significance in measuring liquidity is the bid-ask spread. As can be deduced from the name, the bid-ask spread is the difference between the sell (ask) price and the buy (bid) price of a security. This measure reveals the immediacy cost that investors face when they want to trade instantly (Narasimhan and Kalra, 2014). The types of the latter method include quoted spread, rolls spread, proportional spread and effective spread. Many make use of the quoted spread to avoid any mid-point bias induced by the other measures (Hagstromer, 2021).

This research does not utilise the bid-ask spread because it aims to measures the liquidity for the entire indices or sectoral indices and not individual stocks where bids and asks can be derived. However, acknowledgement is made of how crucial the measure is for other future studies. The Amihud illiquidity measure, also known as the price impact measure, is given by the average daily ratio of absolute returns to daily volume over the month (Narasimhan and Kalra, 2014). According to Amihud (2002), the advantage of this measure is that it is more capable of constructing long time series of illiquidity as compared to the other measures.

Lastly, Granger Causality tests will also be carried out using the Vector Auto Regression (VAR) approach to include the possibility of reverse causality between liquidity shocks and market efficiency (Kim, 2013). Impulse response and variance decomposition analysis will also be employed to visualise and interpret the reaction of capital market efficiency to liquidity shocks and the duration of the shocks.

1.6 Outline of the Research.

The research will be organised as follows; Chapter 2 discusses the underlying theories of liquidity, liquidity shocks and efficiency in capital markets. Chapter 3 engages with the existing studies and empirical findings. Chapter 4 outlines the processes used to collect data and the methodologies used to analyse it. Chapter 5 presents the empirical findings of the research and lastly, Chapter 6 concludes the research and gives recommendations for future studies.

CHAPTER 2

THEORIES UNDERLYING LIQUIDITY AND EFFICIENCY IN CAPITAL MARKETS.

2.1 Introduction.

This chapter will first cover the concepts and theories underlying liquidity and liquidity shocks. The main focus will be the stock market as this is the premise of this research. Additionally, the Efficient Market Hypothesis (EMH), Adaptive Market Hypothesis (AMH), and Behavioural Finance theory are also discussed in relation to stock returns and stock market efficiency.

2.2 Idiosyncratic Risk, Volatility, Liquidity, and Stock Returns.

The concepts of liquidity and liquidity shocks have already been defined in Chapter 1. Here the aim is to go in-depth on understanding how they affect stock returns. In Section 1.2. it was established that there exists a positive relationship between stock illiquidity and expected returns. Here idiosyncratic volatility is used to help understand this relationship better.

Before discussing idiosyncratic volatility, idiosyncratic risk is a much-needed prelude to pave way for a more engaging argument. According to Ooi, Wang, and Webb (2009), idiosyncratic risk (IR) also known as unsystematic risk specific to an asset group and hence can be completely eroded through diversification. However, given the insights by Goyal and Santa-Clara (2003) on how average stock risk is actually driven by IR, developments have been prompted on asset pricing models. As such, financial economists have continued to improve asset pricing theories by introducing new variables or relaxing assumptions such as the effects of a tax on dividends (Malkiel and Xu, 2002). Goyal and Santa-Clara (2003) discuss extensions of the Capital Asset Pricing Model (CAPM) that take into account IR by making provision for investors who hold undiversified portfolios. Furthermore, one also sees how IR would go on to affect cross sectional stock returns in the case that rational investors are to be compensated for failing to hold the market portfolio (Malkiel and Xu, 2002). Note here that idiosyncratic volatility discussed in the following section is derived from idiosyncratic risk.

The influence of idiosyncratic volatility (IV) on expected returns has been a topic of debate in recent literature. As noted with IR, according to Baradarannia, Peat, and Satchell (2015), traditional asset pricing models also leave out the role of IV in pricing assets. Note that IV is defined as the variation in asset returns not explained by asset pricing models (Bali and Cakici, 2008). As such, Malagon, Moreno, and Rodriguez (2018) also highlight that the less precise a pricing model is, the more IV affects asset prices. These models predict that only systematic risk is priced since all investors are assumed to diversify all other forms of risk away. In reality, however, investors do not hold fully diversified portfolios, hence leaving room for IV to be priced into assets.

Although there is a rift on whether IV shares a positive, negative, or insignificant relationship with expected returns, Baradarannia, Peat, and Satchell (2015) provide practical reasoning for this. The latter note that the different conclusions from the literature are mainly a result of using varying portfolio settings. The comparison made here is that value-weighted portfolios show a premium for IV while on the other hand in the case of equally weighted portfolios, IV cannot predict returns regardless of the liquidity factor (Baradarannia, Peat, and Satchell, 2015). The question now in relation to this paper is how liquidity and thus liquidity shocks affect or are affected by both IR and IV and the ultimate impact on stock prices.

Documented theories on liquidity highlight the liquidity premium as an additional expected return required by investors on stocks to compensate them for any potential loss (Sterenczak, 2021). The main theme is that less liquid stocks outperform liquid stocks. This is mainly observed in literature on the United States and other developed economy stock markets (Sterenczak, 2021). More definitively, researchers put forward theories that the liquidity premium is much greater in growing states as compared to economies with stunt growth. However, contrasting arguments have been brought forward noting that liquidity premiums are actually higher in emerging markets when compared to developed markets (Amihud *et al,* 2015).

Adding on, Malagon, Moreno, and Rodriguez (2018) explore the conditional pricing of liquidity concept where during recessions investors prefer to hold more liquid assets such that the price of illiquid assets falls. The latter further note that the existing negative relationship between idiosyncratic risk and expected returns could shift if conditional liquidity regimes were to change. This could explain the contrasting conclusions on the behaviour of liquidity premiums in emerging and developed markets. Another important relationship established is that stocks with high IR are less liquid than low IR stocks. As such, stocks with high IR are actually more sensitive to liquidity shocks (Malagon, Moreno, and Rodriguez, 2018). This is linked to Section 2.2.2 which explores the relationship between liquidity shocks, the stock market, and stock returns.

2.2.1 Liquidity Proxies and the determinants of stock market liquidity.

2.2.1.1 Liquidity Proxies.

Moving forward, it is important to understand the measures of liquidity and its determinants. This section attempts to do that. Like a majority of economic variables, liquidity is not directly observable thus researchers make use of proxies to estimate its relationship with financial market variables such as asset prices and market efficiency in this research. Given that liquidity has multiple dimensions, this goes on to explain how there are a number of proxies used to measure liquidity. In Chapter 1, Section 1, the dimensions of liquidity (depth, tightness, immediacy and resilience) are listed. Here, the aim is to shortly discuss these characteristics and thus better understand where they fit in terms of the liquidity proxies.

- Depth is outlined as the ability to trade (buy and sell) an asset without changing or influencing the quoted price drastically (Narasimhan and Kalra, 2014). More practically, depth indicates the total quantity of bids and asks required to change prices of the market order book. As such, one could say that the number of units offered at the ask price plus those offered at the bid price reflects the depth of a market at a point in time. According to Sarr and Lybek (2002), volume-based measures such as the trading volume are proxies used to indicate the level of depth in a market.
- Tightness reflects transaction costs. Narasimhan and Kalra (2014) define tightness as the ability to buy and sell an asset at the same price in the same time period. The measures for this dimension of liquidity can be any type of bid-ask spread measure such as the quoted spread for example.
- Resiliency looks at the ability of asset prices to recover after a sudden shock and thus come to a new equilibrium. Additionally, this liquidity dimension also takes into account the asset price elasticity of supply and demand into account (Narasimhan and

Kalra, 2015). Sarr and Lybek (2002) note that both the price impact measures and the equilibrium price-based measure account for the resiliency dimension.

- Immediacy indicates the speed at which large volume transactions can be cleared in a given market (Sarr and Lybek, 2002). Therefore, immediacy focuses on the time it takes to find a buyer or a seller for large volume transactions. The latter note that immediacy is made possible by dealers ever ready to buy and sell large volumes of an asset at the quoted prices. The imputed round trip cost and Huang and Stoll's price impact measure account for this dimension.

As can be noted above, no single measure can adequately capture all the dimensions of liquidity. Literature shows that there are about 68 liquidity measures used by researcher's world over (Aitken and Winn, 1997). Therefore, the variety of proxies are grouped as follows to better capture each liquidity dimension (Note, it is possible that a liquidity proxy captures more than one dimension, but not all); volume-based, price impact, and transaction cost measures (Sarr and Lybek, 2002). All of these are explained below.

- *Volume-Based Measures.*

According to Sarr and Lybek (2002), volume-based proxies are most useful in measuring the depth and breadth of a securities market. Adding on, Le and Gregoruou (2020) note that volume measures can distinguish the levels of liquidity by the number of transactions executed during a particular period in time. More so, the number of transactions provides information to dealers about their position and risk in the market. For example, large transaction volumes entail a high number of bids and ask prices as such, dealers can execute orders with minimum risk. Since dealers source information from a large volume of trades, Sarr and Lybek (2002) suggest that in the case of lower volumes and thus diminished market depth and breadth, the result could be uncertainties about equilibrium prices. Such a situation can dry up the volume further.

An interesting aspect about this proxy is its positive relationship with the bid ask spread. Indeed, literature notes that a large bid-ask spread indicates low volume and thus illiquidity. Furthermore, increased volume induces price discovery which reduces the spread (Le and Gregoriou, 2020). Now, there are two common volume-based proxies: trading volume and the turnover ratio. The trading volume liquidity proxy is easy to calculate, mostly using dollar trading volume. The proxy is widely used because it is easy to interpret, high trading volume simply indicates high liquidity. However, the trading volume proxy's demerit is double counting (Sarr and Lybek, 2002). As such, the turnover ratio proxy which captures trading frequency is considered more suitable comparatively. For this reason, this research makes use of this measure to proxy liquidity shocks as described in Chapter 4. The latter is calculated as the number of shares traded divided by the number of outstanding shares (Le and Gregoriou, 2020).

- *Price Impact Measures.*

The Amihud illiquidity and Amivest measures are the two main proxies in this category. Developed by Amihud (2002) the Amihud measure indicates the price shock triggered by changes in the unit dollar volume. Absolute daily stock returns data for every share on an index is used to estimate illiquidity while, "the impact of each share is weighted by its free float rate and market capitalisation" (Kumar and Misrar, 2015). Literature notes that the Amihud measure's robustness stems from its ability to capture minimum changes that is minimum tick size. However, the demerit of the latter is that it does not include days without trading. Adding on, the Amivest measure which is mainly critcised for excluding days with zero returns was introduced by Cooper *et a*l (1985). Here, volume is measured using the number of shares as opposed to the dollar volume in the Amihid measure. As can be easily deduced, another difference between the two measures is that the Amivest measures liquidity while the Amihud measures illiquidity (Kumar and Misrar, 2015).

- *Transaction Cost Measures.*

Le and Gregoriou (2020) define transaction costs as expenses incurred by market participants when assets are traded. In the same light, Sarr and Lybek (2002) indicate the importance of the bid-ask spread proxy in capturing both implicit and explicit costs of trading. Implicit costs are not easy to identify but bid-ask spreads and sizes of transactions for example capture their components. Explicit costs, however, are easily observable and include brokerage fees and taxes (Le and Gregoriou, 2020). In dealer markets, the bid-ask spread can reveal order processing, asymmetric information, and inventory carrying costs. Pre-trade transaction costs are measured by the quoted spread which is the average of two quotes at a particular point in time (Kumar and Misrar, 2015). Furthermore, the latter also note that transaction costs incurred by investors are accurately captured by the effective spread which divides the absolute difference between the transaction price and the quote midpoints at the time of a transaction by the transaction price.

- *Other proxy classifications.*

Aitken and Comerton-Forde (2003) take a different approach in grouping liquidity proxies. According to the latter, all proxies fall under two main categories which are the trade based and order-based measures. Trade based proxies are calculated using trading value, trading volume and the turnover ratio. According to Aitken and Comerton-Forde (2003), trade-based measures are attractive due to the availability of data thus are widely accepted by market participants and researchers. However, these measures fail to capture immediacy costs which are an important aspect of liquidity. Another demerit of the measure is its ex-post nature meaning that it indicates past trades only. On the other hand, order-based measures are recorded to accurately capture the costs of trading immediately. Note that the bid ask spread and price impact measures are the main proxies in this category. The main takeaway is that the bid-ask spread accurately measures liquidity in the case of small traders. When it comes to institutional traders, the spread measure has a high chance of underestimating the costs of trading and thus overestimating liquidity (Aiteken and Comerton-Forde, 2003).

Furthermore, Le and Gregoriou (2020) note that liquidity proxies can also be captured using transaction data frequency and thus grouped under high-frequency and low-frequency measures. The major difference between the two strands being that intraday data is used in high-frequency proxies while low-frequency proxies make use of daily data. As such, according to Goyenko *et al* (2009), high-frequency proxies are most applicable to developed stock markets due to the large data samples which require high-end skill and advanced computer programming to analyse. Low-frequency proxies, however, require easily accessible data which makes them viable for both developed and emerging market analysis. One can also add that low-frequency proxies stand superior since they are more suitable for cross-country liquidity studies.

2.2.1.2 Determinants of stock market liquidity.

Given the consensus that liquidity is mostly beneficial to financial markets, it is imperative that a discussion on its determinants also be had. Kumar and Misrar (2015) indicate that the determinants of liquidity can be grouped into macroeconomic factors and firm specific factors. The latter firstly stresses the role of institutional ownership with regard to stock market liquidity. Here the takeaways are that institutional ownership can improve informational benefits and price discovery through competition which overall improves stock market liquidity and efficiency. Macroeconomic factors that improve stock market liquidity include, foreign investment inflows and international listings (Naik and Reddy, 2021). Adding on, Kumar and Misrar (2015) review literature that shows that earnings announcements in an imperfect (informationally inefficient) market increases information asymmetry and thus reduces liquidity. Updating stock market infrastructure such as algorithmic trading also improves liquidity. The logic here is that better algorithmic trading systems reduce trading costs and frictions which ultimately increases efficiency and liquidity.

Wuyts (2007) introduces transparency, anonymity and tick size as stock market-specific determinants of liquidity. Transparency is the ease at which market participants can access and observe information about the trading process (Wuyts, 2007). Transparency has an effect on how the dealers perceive the market and thus impacts the rate of order submissions which also directly influences liquidity. The argument however is that market participants are not the same. As such, given a situation whereby informed traders prefer less transparency as opposed to uninformed traders, the effect of transparency on liquidity becomes uncertain.

Anonymity which is closely related to transparency is the degree market participant identities are revealed to other participants (Wuyts, 2007). Most literature shows that concealing participant identities increases illiquidity since it becomes hard to now distinguish between informed and uninformed traders. However, the problem is the same with transparency because some participants thrive in markets where identities are concealed. More so, Wuyts (2007) also discusses how a reduction in tick size decreases spreads and thus improves liquidity. Here the tick size is the minimum movement in the price of a share. Note that the determinants of stock market liquidity discussed here are not exhaustive.

2.2.2 Liquidity Shocks and Stock Returns.

It is important to note that there exists very little literature and theories on the relationship between liquidity shocks (defined as sudden changes in liquidity levels in Section 1) and the stock market. However, Amihud and Mendelson (1986) provide the initial forms of literature on liquidity and asset returns. From their work stems most of the literature that looks into how cross-sectional returns are influenced by time-varying liquidity hence liquidity shocks (Stefanovski and Rasin, 2013). Retrospectively, the global financial crisis managed to increase attention on understanding more about the mechanics of the stock market and variables that affect it including liquidity shocks. Dang *et al* (2014) pave way for such a discussion when they look into the transmission of liquidity shocks through different channels. In relation to this, Ma, Anderson, and Marshall (2018) note that liquidity actually serves as a channel for market volatility to affect stock returns. More specifically, the latter reveals that liquidity shocks have a much greater impact on stock returns as compared to market volatility shocks. Adding on, the literature reviewed by Dang *et al* (2014) suggests that ownership of stocks by institutions could have been the main reason for the liquidity shock contagion effect in stock markets across the world. This becomes a concern because shocks to financial assets lead to increased risk aversion and hence stringent risk management measures which could entail disinvestment from capital markets altogether (Dang *et al*, 2014).

Adding on, the literature has mostly dwelled on how the stock market underreacts to stock-level liquidity shocks (Bali *et al*, 2014). More so, according to Jang (2022) literature in South Korea points out that when the stock prices do not promptly respond to a stock-level liquidity shock (just liquidity shocks from here onwards), this can indicate weak market efficiency. The latter also discusses two sources of market frictions that lead to stock market underreaction: illiquidity and limited investor attention. Illiquidity inhibits investors from immediately trading based on new information. Bali *et al* (2014) also agrees and notes that the slower adjustments in stock prices in the event of liquidity shocks are caused by illiquidity since illiquid stocks are harder to trade thus clouding price discovery. Additionally, limited investor attention distorts information processing by investors in the presence of other market frictions. According to Bali *et al* (2014), liquidity news can be very elusive thus compromising investor attention even more. As such, this goes on to prove Peng and Xiong's (2006) model that even when investors maximise their attention, most of that attention goes to systematic shocks as compared to stock-specific shocks which stem from IR discussed in Section 2.2. This makes a strong case as to why investor attention causes underreaction to liquidity shocks.

Furthermore, liquidity is known to be time-varying and, as been discussed, subject to shocks that have spill over effects. Bali *et al* (2014) indicate that liquidity shocks are not only positively related to the returns on stocks with similar risk profiles (contemporaneous returns) but also predict future returns. The latter also added that persistent negative liquidity shocks would result in low contemporaneous returns but high future returns. Adding on, Jang (2022) notes that the liquidity shock effects on future returns are rather short-lived and dissipate within two to 6 months. Literature studies also state that the positive relationship between liquidity shocks and future stock returns is mostly significant for illiquid stocks as compared to liquid stocks (Jang, 2022). On that note, Bali *et al* (2014) highlight that the latter relationship may not hold or be significant in an inefficient market. Given that liquidity shocks are generally not well defined to the average investor, it becomes harder to interpret their pricing implications. As such, it is important to gain more understanding of how stock markets react to liquidity shocks and thus unpack how different markets process information about liquidity shocks. This can also go on to reflect the extent of efficiency in these markets.

2.3 The Efficient Market Hypothesis.

The efficient market hypothesis (EMH) remains a useful benchmark for regulators of financial markets although having faced a lot of criticism over the past decades (Farkhry, 2016). As the cornerstone to understanding and explaining modern asset pricing over the last half century, the EMH is premised on asset prices reflecting all available fundamental and non-fundamental information (Fama, 1970). As such, according to the EMH, an ***efficient market*** is one where all available information is fully reflected in prices.

Malkiel (2003) notes that the EMH is strongly associated with the random walk series. This entails that price changes continue to deviate further and further away from the mean when one looks at an asset price series. Put simply, price changes are independent of their past value. Ultimately, what will be seen is a market where information is accurately and immediately reflected on asset prices (Malkiel, 2003). In such a market, future price changes reflect only future news. Farkhry (2016) highlights that since news is unpredictable, then future prices also become unpredictable and random. In agreement with this, Beukes (2010) notes that asset price changes have no memory meaning that past trends could not be used in a meaningful way to predict future trends.

Additionally, other theories of the EMH that support the Random Walk Model include the Fair Game Model and the Submartinagale model. The Fair Game Model, according to Naseer and Bin Tariq (2015) shows that asset price equilibrium can be shown in terms of expected returns. As such, the equilibrium expected return is actually a function of the risk associated with an asset. Note that a situation whereby investors earn a return consistent with risk is in this case 'fair game'. Additionally, the market is efficient in the latter model due to the large volume of transactions which quickly move prices back to equilibrium incorporating all available information (Naseer and Bin Tariq, 2015). Adding on, Fama (1970), indicates that the price sequence of an asset follows a submartingale with respect to an information sequence.

Therefore, the submartingale model looks at how prices in future periods are expected to be greater than those in the current period. This means that knowledge of past events on prices cannot assist in predicting future values (Naseer and Bin Tariq, 2015).

Furthermore, Farkhry (2016) puts forward that the EMH falls short mostly due to its neoclassical-based assumptions. These include investors and institutions being rational, profit maximisers, and risk averse. The EMH also assumes that arbitrageurs' actions of buying undervalued assets and selling overvalued assets eliminates any gains to zero. However, Malkiel (2003) highlights that arbitrageurs are also capable of taking advantage of the market thus driving prices further away from the equilibrium price.

The main conclusion, and what brings the most criticism to the EMH is that no one can beat the market (Fama, 1970). Here, the notion is that no amount of investor foresight and use of portfolio management strategies, technical or fundamental analysis will enable such an investor to earn excess adjusted returns (Malkiel, 2003). In fact, the only way to earn above-average returns is for an investor to accept and incur above-average risk. This brings us to the three forms of the EMH: weak, semi-strong and strong form.

- According to Fama (1970), the weak form considers that asset prices adjust immediately to new information on historical prices. As such, it is not possible for an investor to beat the market using technical analysis. However, in the short run, investors can use fundamental analysis to earn above-average adjusted returns. Another important point to note is that the weak form market efficiency is satisfied when the difference between observed and expected returns is zero (Milionis and Moschos, 2000)
- The semi-strong form states that prices fully incorporate all publicly available information such as earnings, mergers and acquisitions, stock splits, and political and economic events (Fama, 1970). According to Jang (2022), well-developed economy stock markets are regarded as semi-strong form efficient. In support of the latter, Naseer and Bin Tariq (2015) highlight that information regarding stock splits is immediately reflected in the stocks concerned at the time the stock split occurs.
- The strong form proposes that all available information (public and private) is incorporated in asset prices such that no one investor has monopolistic access to any private information that allows them to earn above-average adjusted returns (Fama, 1970).

It is important to note that markets can still be regarded as efficient even when a significant portion of market participants are regarded as irrational (Malkiel, 2003). Beukes (2010) agrees with the latter noting that efficiency does not require every market participant to be rational, but rather to follow a normal distribution pattern such that the net effect of all activity on prices still eliminates gains to zero. More so, even markets with high volatility can still be regarded as efficient as long as they reflect new information rapidly and do not allow investors to earn above-average returns (Malkiel, 2003). Fama (1965) firmly reassures that the EMH upholds in the long run since the overaction or underreaction of market participants is not significant.

2.3.1 Stock Market Efficiency in Relation to the EMH.

In the previous section, the EMH in relation to overall financial market efficiency was covered. Now, the aim is to narrow down and discuss the literature on efficiency with regard to stock markets specifically. Some of the earliest work on the subject is presented by Kendall (1953) who notes that there was no way to predict the returns of the United Kingdom Stocks. Adding on, Malkiel (2003) argues that stock markets are far more efficient and thus less predictable when compared to other financial assets. The latter points out that although stock market price behaviour is erratic at times, the market is very much efficient and does not allow investors to earn above-average returns. Adding on, Chan, Gup, and Pan (1997) indicate that monthly stock prices actually follow a random walk model and categorised them as weak form efficient. This is in contrast to Jang (2022) who identified that stock markets in developed economies are semi-strong efficient. Note here that the literature presents irrefutable evidence that stock markets are indeed efficient, but it certainly does not go uncontested.

Lim and Brooks (2011) review literature that shows stock returns being predictable, overreacting to information, and the profitability of using technical trading strategies in stock markets. In support of the latter, Filis (2006) indicates stock market anomalies such as the 'January Effect' and the 'weekend effect' that make stock market returns even more predictable. This has been shown to be mostly true for emerging stock markets. Such literature puts into question the efficiency of the stock markets. As such, more recent studies have looked at the evolving efficiency over time. This is to be expected given the improvement in trading technology, changing regulations, and market structures over time. Ito and Sugiyama (2009) note that US stock market efficiency has been wavering over time. In this regard, one may analyse and say that stock markets have been losing efficiency over time and thus becoming less efficient (Lim and Brooks, 2011).

One thing is for certain when reviewing the literature on financial market efficiency, the EMH and behavioural finance schools have no middle ground. As such, the go-to theory is the Adapted Market Hypothesis brought forward by Lo (2004) which consolidates the two theories into one. This is covered in Section 2,5.

2.3.2 Liquidity and Efficiency.

The recurring flow of thought as noted above when it comes to liquidity and how it affects market efficiency is that lower liquidity discourages investors from engaging in large volumes of transactions due to a higher risk of incurring losses. This has the effect of drying up capital inflows which ultimately stunts financial market development leading to both intraday and informational inefficiency (Kumar and Misra, 2015). It is important to note that in the short run, informational inefficiencies can be observed. This is mainly due to the time investors take to absorb new information before acting on it. As such, in literature, a consensus that stock returns are predictable from technical analysis in the short run is reached (Chordia, Roll, and Subrahmanyam, 2008). However, according to Chordia, Roll and Subrahmanyam (2008), return predictability in the short run should be diminished in periods when the market is more liquid. In other words, higher liquidity in this case actually improves efficiency.

Adding on, Chung and Hrazdil (2010) also highlight that a negative relationship could exist between liquidity and efficiency if market makers fail to act on new information. The logic here is that the market makers in such cases will face adverse selection and thus liquidity will dwindle. At the same time, other market participants are incentivised to look for information increasing the informational efficiency of the market. It is also important to highlight that prices are also expected to efficiently reflect the liquidity risk premium as outlined by Sterenczak (2021). What is not known and perhaps left to discover is how market efficiency could possibly react to drastic changes in liquidity (liquidity shocks).

2.4 Behavioural Finance and Stock Market Efficiency.

The efficient market hypothesis no longer enjoys the level of support it did in the golden era since the mounting criticism by the school of behavioural finance put into question the basis of its relevance (Lim and Brooks, 2011). Ritter (2003) indicates that behavioural finance (BF) is a paradigm that when compared to EMH looks through a wider theoretical window. In agreement, Shiller (2003) sees BF as finance viewed from a broader-based social science with aspects of sociology and psychology. Two building blocks are mainly used to critique the legitimacy of efficient markets: cognitive psychology and limits to arbitrage (Ritter, 2003). Cognitively, market participants exhibit patterns such as overconfidence which spews reckless risk-taking and conservatism thus underreaction or overreaction to market changes and even new information.

All in all, the gist here is that market participants make systematic errors that create distortions and ultimately result in inefficiency (Ritter, 2003). Limits to arbitrage occur in markets where misevaluations do not attract arbitrageurs to enter the market due to high risks of incurring losing streaks on their positions. With no arbitrageurs in the market bringing gains to zero, above-average returns are earned and thus rendering such a market inefficient. Adding on, Shiller (2003) makes use of the volatility anomaly to debunk efficiency in stock markets. Here, the latter notes that excess volatility above that which is predicted by the EMH is observed in stock markets, therefore price changes occur due to ‘animal spirits. This means that information is not adequately reflected in prices.

Note that Behavioral Finance blossomed as a result of anomalies sprouting out of traditional finance models. As such, BF steps in and finds logical explanations for these anomalies using models such as the feedback mechanism (Shiller, 2003). The example of an asset speculative bubble is used by most researchers to illustrate how expectations from investors go back and forth leading to either an upward or downward spiral of the assets’ price hence the feedback mechanism. The justification from BF points out that poor human judgements and heightened expectations explained by cognitive psychology result in these anomalies. In other literature, what we see here is referred to as representative bias. Shiller (2003) explains that in this case, informed investors over-rely on recent patterns and negate actual available information provided by the market.

Adding on, in agreement with the latter, Daniel, Hirshliefer and Subramanyam (1997) add two behavioural biases that contribute to financial market anomalies. Overconfidence, much like representative bias, sees informed traders over-emphasise the precision of their knowledge about stock prices. Consequently, the self-attribution bias has traders choose their own perceived stock value as opposed to that perceived from public information, especially if the two contradict (Fama, 1997). The takeaways here are that BF highlights the importance of market participants in how their actions influence the markets over time. As such, the market and its participants are inseparable when defining the outcomes and thus evaluating degrees of efficiency (Birau, 2012).

To sum it all up, notice that BF rests mostly on dispelling the classical economic theory of rationality. As depicted by Shiller (2003) earlier in this section, BF fully embraces that investors seldom behave rationally but more subjectively and thus more ground to reject the EMH.

2.5 The Adaptive Market Hypothesis and Stock Market Efficiency.

The ground breaking work on the Adaptive Market Hypothesis (AMH) was mostly done by Lo (2004) who adopted the concepts of 'satisficing' and bounded rationality from Simon (1955). Satisficing speaks to how market participants do not necessarily make optimal (maximising) decisions as suggested by the EMH but rather make satisfactory decisions which are more aligned with their abilities and knowledge at certain points in time. In the same light, bounded rationality points down the idea of rational expectations given that rationality could only be optimised if market participants all had adequate knowledge and abilities at all times. Lo (2004) thus proposes a new framework for looking at financial market efficiency that reconciles the EMH and Behavioural Finance and takes into account the evolutionary perspective of the markets and their participants. Some of the core aspects of the AMH as outlined by Lim and Brooks (2011) include market participants learning and adapting over time, the existence of competition in the markets drives innovation and adaptation while the evolution of the markets shapes their dynamics.

When looked at from another perspective, the AMH can be said to bring out varying levels of market efficiency through time (Dhankar and Shankar, 2016). In support of this, Lo (2012) points out that the relevance of the EMH was affected by timing. Indeed, during the 1940s to early 2000s, the financial market environment was graced with low risk and volatility hence its wide acceptability and viability of buy and hold strategies. This has since changed as we now see stochastic trends in the financial markets (Lo, 2012). The implications of the AMH as highlighted by Dhankar and Shankar (2016) are thus as follows; (i) market participants' preferences have an effect on the risk-reward relationship, (ii) changing investor population over time entails that market efficiency is not a steady state, (iii) arbitrage opportunities exist in low-efficiency states, (iv) investment strategies do achieve above average returns in certain environments. With this in mind, one could safely conclude given the varying market efficiency that gives different returns over time that the use of active portfolio management by investors is justified.

2.6 Chapter Summary.

This chapter has successfully outlined the important literature and theories surrounding liquidity, liquidity shocks and efficiency. Section 2.2 highlighted the shortcomings of traditional asset pricing models by introducing idiosyncratic risk and volatility. It was made clear in the literature that unsystematic risk factors do indeed influence stock prices, especially in recent times. This is where the effects of liquidity shocks on asset prices and ultimately stock market efficiency fit in. Additionally, the chapter also discusses the complex relationship between liquidity shocks and stock market returns. Here, Bali *et al* (2014) and Jang (2021) provide most of the literature on how the stock markets actually underreact to liquidity shocks due to market frictions and the evasive nature of liquidity news. More important takeaways from the chapter include the positive relationship between liquidity shocks and stock returns. The more debatable aspect is that liquidity shocks predict future returns in the short run.

The Efficient Market Hypothesis, Behavioural Finance, and the Adaptive Market Hypothesis stand as theories giving legitimacy and direction to the literature covered in this chapter. In terms of the stock market, we end the chapter knowing that some developed markets exhibit semi-strong form stock markets while weak form efficient stock markets are prevalent in emerging markets. More interestingly, time is clearly indicated to play a major role when it comes to efficiency. Firstly, it is noted that over time stock market efficiency varies and secondly that in the short-run, stock markets exhibit inefficiency especially if the market is illiquid. Behavioural finance comes in and debunks most of the EMH assumptions, especially the notion that investors cannot beat the market. Ultimately, the two schools of thought are brought together in the AMH where Lo (2004) reconciles ideas from both models and suggests an evolutionary approach to financial market efficiency.

CHAPTER 3

EXISTING EMPIRICAL FINDINGS

3.1 Introduction.

The evolution of financial economics has meant more ground breaking findings, especially for stock markets. As such, the research will attempt to tap into this body of knowledge in search of relevant empirical findings to support or debunk aspects of efficiency, liquidity and liquidity shocks and how they relate to stock markets in developed markets (United States (U.S), the United Kingdom (UK), Japan as compared to developing markets (Africa, Asia and Latin America). The choice of countries is based on the location of the biggest stock exchanges in the world and in Africa. Lastly, the chapter also provides findings on the accuracy of the Amihud (2002) illiquidity measure, the bid ask spread measure and trading volume.

A few pointers before delving into the findings. Given that the research aims to determine the impact of liquidity shocks on stock market efficiency (SME), Section 3.2 and 3.3 proceed first by discovering the existence and thus state of SME across different markets. Note here that one of the questions to be answered by the research in Chapter 5 is whether liquidity shocks will improve or worsen SME. Therefore, to gauge the existing state of SME, the EMH, a widely accepted measure of SME as seen in Chapter 2 is utilised. Adding on, testing the EMH is also relevant to the research due to the fundamental problem discussed in section 1.2. Here it is highlighted that liquidity shocks may not be adequately reflected in stock prices if informational efficiency is absent or the EMH is not met (Bali *et al*, 2014).

3.2 Evidence of Stock Market Efficiency in Developed Markets.

From Chapter 2, Malkiel's (2003) paper already points out that stock markets are for the most part efficient. Other supporting literature also noted that stock markets are weak-form efficient. Additionally, it was also discussed that unlike in most developed markets developing economy stock markets fail to follow a random walk process and thus are for the most part regarded as inefficient. However, Ito, Noda and Wada (2016) who employed a time-varying Auto-Regressive model to evaluate stock market efficiency in the U.S indicated that the rejection of a random walk process does not rule out the validity of the EMH and shows very little about the degree of efficiency in a particular stock market. This is important to keep in mind as these findings are explored. Now, the aim is to review specific findings for a sample of countries whose stock markets are studied most due to their size and performance.

3.2.1 Findings in the United States.

It will be noted that most findings point out that U.S stock markets follow a random walk process and thus are weak form efficient. In support of this stance, Ito, Noda and Wada (2016) deduced that U.S stock markets were mostly efficient in their period of study at the 1% level of significance. The latter concluded that stock market behaviour is very much consistent with the Adaptive Market Hypothesis (AMH) since their findings showed cyclical fluctuation in the degree of efficiency over time. It is however noted that in the 1930s and three other periods of economic recessions, the degree of market efficiency significantly fell in the U.S. One of the most important findings by Ito, Noda and Wada (2016) is that no significant evidence showed stock market inefficiency after 1958. Reasons for this could be better investor experience and technology advancement in the markets. In agreement with the latter, Rodriguez *et al* (2014) find similar results pointing out that U.S stock markets became more efficient from 1972 onwards on average. Another similar discovery was that stock markets indeed support the AMH since Rodriguez *et a*l (2014) also find that market efficiency did vary over different time scales.

Rodriguez *et al* (2014) used the Detrended Fluctuation Analysis method (DFA) to investigate SME over different time scales in the U.S. Their results show that the degree of SME is a function of the time scale. Using the scaling exponent, the latter discovered that U.S stock markets adapt to external shocks (financial, social, political and economic shocks). Furthermore, it is evident from their research that when markets fail to adapt to shocks timeously, return predictability peaks and thus efficiency dwindles significantly. Choi (2021) who also used the DFA, conducts a more decentralised approach to testing SME during the global financial crisis and the COVID-19 pandemic. The latter made use of sector analysis and found that the consumer discretionary stock market sector was the most efficient in both periods. Low efficiency, or inefficiency rather, was found to be prevalent in the utilities stock market sector. The conclusion made here is that the utility sector is highly regulated and gives high dividend pay-outs, hence more suitable for investment during periods of crisis (Choi, 2021)

Furthermore, Seth and Sharma's (2015) paper also explored the possibility of completely inefficient U.S stock markets. The main finding here was that U.S stock markets are inefficient and thus give way for investors to use investment strategies and make above-average returns. Furthermore, the latter outlined that most U.S and Asian stock markets do not follow a random walk process and that financial shocks in the economy had no effect on SME. Another significant finding in this study was that over time, U.S and Asian stock markets were correlated, and thus international portfolio diversification would not yield additional returns. By making use of the GARCH (1,1), evidence of volatility clustering was found in U.S markets which is said to indicate inefficiency (Seth and Sharma, 2015).

3.2.2 Findings in the United Kingdom and other parts of Europe.

Some of the earliest work to test SME in the UK was conducted by Darrat (1987) who used the monetary portfolio theory to explain the relationship between stock prices and money growth and thus infer efficiency. The tests conducted assessed how quickly stock prices incorporated news of changes in money growth applied by the monetary policy. The results from the latter showed that the UK and West Germany stock markets were inefficient in the period 1960-1982. Darrat's (1987) results indicated that significant lags were observed in the reaction of stock prices to changes in money growth. For the other European stock markets, the serial correlation coefficient tests indicated mean reverting stock returns hence proving them to be weak form inefficient (Worthington and Higgs, 2004)

On a more positive note, a significant number of empirical findings point to some efficient European stock markets. Worthington and Higgs (2004) tested the efficiency of 16 European stock markets including the UK using a combination of methods including, serial correlation coefficients, run tests and multiple variance tests. Of the markets tested, only Germany, Ireland, Sweden, Portugal and the UK followed the random walk process and thus were efficient. Similar findings are seen in the Rounaghi and Zadeh (2016) paper where the ARMA model is used to forecast monthly and yearly time series stock returns. The latter found that the London Stock Exchange (LSE) was indeed efficient and stable during cyclical changes in the economy. Adding on, Milionis and Moschos (2000) also found that the LSE to be weak-form efficient. Unit root tests conducted on 18 European stock markets including those in the UK showed that stock prices were stationary in first difference terms indicating that individually, the markets were weak form efficient (Chan, Gup and Pan, 1997).

3.2.3 Findings in Japan.

Stock market efficiency in Japan has been most talked about since the implementation of the Arrowhead Renewal Improvements (ARI) in 2015. ARI meant the enhancement of the Tokyo Stock Exchange (TSE) trading system mainly in terms of high-frequency trading and risk management functions (Kemme, Mclnish and Zhang, 2022). An interesting finding from the latter is that even after improving trading systems on the TSE, market efficiency did not improve significantly. An earlier study by Nagayasu (2003) also on the TSE notes that over time market efficiency did not improve after reforms such as liberalisation and deregulation of capital markets in Japan. Using the ARFIMA-FIGARCH model, it was observed that TSE return data had ARCH effects and thus evidence against the EMH (Nagayasu, 2003).

Furthermore, to test for informational efficiency, Du (2021) made use of the sentiment index, surprise index and the ARCH model to investigate reactions of returns on the Nikkei 225 to public information (good and bad news). The results show that the returns of the Nikkei 225 closing price were significantly impacted by both positive and negative news between 1998 and 2017. Du (2021) adds that the Nikkei 225 closing prices reflected negative news much more efficiently than positive news. This is mainly a result of the bursting of the 1991 bubble in Japan which led to pessimistic sentiments influencing investor strategies. Thus, Du (2021) explains that Japan's capital market behaviour can be explained by the loss aversion theory. Adding on, Tsutsui and Hirayama (2004) analyse how well the U.S and Japanese stock markets respond to each other's movements. The latter found that both the New York Stock Exchange (NYSE) and the Tokyo Stock Exchange had improved response times between the markets. More specifically, it was found that the mean reaction time for Japanese markets was about 6 minutes to the US market movements while the US market's response time was an average of 14 minutes. This is further evidence of informational efficiency in both Japan and the US.

3.3 Evidence of Stock Market Efficiency in Developing Markets.

The literature in Chapter 2 indicated that emerging stock markets would most likely be inefficient. However, Yilmaz (2001) debunks this notion highlighting that emerging stock market development experienced mostly in the 90s has yielded more efficient markets. This is once again in agreement with AMH discussed in Chapter 2 noting that efficiency improves over time. A study of 21 emerging stock markets by the latter between 1988-2000 showed that market efficiency significantly improved except for Mexico and East Asian markets that experienced financial crises in the same period. Furthermore, Nurunnabi (2012) conducted a review of weak form efficiency tests done across the world and notes the efficiency of some emerging markets despite having poor levels of liquidity and institutional infrastructure when compared to developed markets. This section will reveal per-country evidence of whether emerging stock markets are indeed efficient.

3.3.1 Findings in Asian Markets.

- *China*

In China, the top-performing stock indices include the Shanghai and Shenzhen indices. Additionally, also note that China makes use of multiple classes of shares for example A shares and B shares (Beltratti, Bortolotti and Caccavaio, 2016). Liu (2011) made use of non-parametric independence tests and unit root tests to evaluate the efficiency of these indices between 2002 and 2009. The unit roots tests conducted indicated that all the indices were weak form efficient. On the other hand, however, non-parametric independence tests had some mixed results. The null hypothesis of a random walk is not rejected at the 1% level for the Shanghai index A and the Heng Seng index hence efficiency. Adding on, tests conducted for all daily and weekly indices pointed at weak form inefficiency (Liu, 2011).

Chong, Cheng and Wang (2010), also find mixed results for Chinese stock markets when they tested for SME in the BRICs countries. Using a basket profitability trading tests as indicators of efficiency, the latter made the conclusion that buy and hold strategies in Chinese stock markets could earn above average returns and thus beat the market. Samaratunga (2009) also reached the same conclusion noting that 7 of the 8 Asian Pacific region stock markets were inefficient, China included. On the other hand, evidence from Lim *et al* (2013) points out that the Shanghai (both A and B) indexes and the Shenzhen A are weak form efficient. Run tests and Serial correlation tests reinforce each other in failing to reject a random walk hypothesis in all indices except the Shenzhen B.

- *Findings in other Asian Markets.*

While testing the impact of financial liberalisation on SME, Rejeb and Boughrana (2013) found that financial liberalisation improves not only informational efficiency but also reduces financial crisis occurrences. As such, the latter found results showing that past returns were independent of future returns, hence efficiency in 10 out of the 13 emerging markets tested. In terms of inefficiency, this included the Philippines which was found to have predictable returns. Additionally, it is also noted that efficiency varies across markets depending on the size, liquidity and openness of each market (Rejeb and Boughrana, 2013).

For the Bombay Stock Exchange (BSE) in India, Poshakwale (1996) made use of the run and autocorrelation tests and concluded that the market was weak form inefficient. Mukherji (2015) agreed with the latter after using a country-specific Vector Autoregression model and also finding inefficiencies in the Indian stock markets. Nurunnabi (2012) reviewed two contradicting studies in India. The first tested weak form efficiency for the BSE and NSE and found inefficiency in both markets. The other study by Sharma and Kennedy (1977) concluded differently that the BSE is actually weak form efficient.

Adding on, Mobarek, Mollah and Bhuyan (2008) tested the returns of the Dhaka Stock Exchange (DSE) using both non-parametric tests (normality and run tests) and parametric tests (Autocorrelation tests, Autoregressive and ARIMA models). All tests rejected the possibility of a random walk hypothesis in the DSE returns and thus pointed at weak form inefficiency. The DSE was again found to be inefficient by Hassan, Islam and Basher (2000) and Ahmed (2002). In contrast, however, Nurunnabi (2012) highlights a study using variance ratio tests which found that the DSE followed the random walk model and thus would be considered efficient.

3.3.2 Findings in the African Markets.

For the African stock markets, evidence also shows that efficiency has been changing and mostly improving over time. It is identified that these emerging markets interchangeably go through inefficiency and efficiency over time. Smith and Dyakova (2014) summarise that the least predictable stock markets are found in Egypt, South Africa and Tunisia, while the most predictable and thus inefficient markets were in Kenya, Zambia and Nigeria. By making use of the rolling windows method, it is identified that of the 8 countries tested, Kenya and Zambia were the most informationally inefficient (Smith and Dyakova, 2014). Additionally, predictability for the South African and Tunisian markets is found to be statistically insignificant.

A surprising degree of weak form efficiency is also found in the African stock markets by Magnusson and Wydick (2010) who tested 8 of the largest markets in Africa. The latter failed to reject the random walk model for the stock markets in Botswana, Côte d'Ivoire, Kenya, Mauritius and South Africa. However, stock markets in Ghana, Nigeria and Zimbabwe were found not to follow the random walk. Magnusson and Wydick (2010) also noted that when compared to other emerging stock markets (in Latina America and Asia), African stock markets showed a great deal of improvement in terms of efficiency. A Similar study is conducted by Ntim *et al* (2011) using variance ratio tests to examine the efficiency of 32 African stock indices. In this case, however, the null hypothesis of a random walk model is rejected for all indices at the 1 % level. The conclusion of this paper was therefore that African indices have predictable returns and are thus inefficient. It is further highlighted that African markets in the period of study averaged liquidity ratio results of about 30 %. These low levels of liquidity are most likely the cause of market inefficiency (Ntim *et al*, 2011).

Furthermore, Muragu (1990) tested the independence and randomness of share price returns of the Nairobi Stock Exchange (NSE). The serial correlation tests employed by the latter found no significant coefficients for about 12 lags indicating inefficiency for the NSE. These results are consistent with findings in Kenya discussed earlier (Magnusson and Wydick, 2010 and Smith and Dykova, 2014). The Gimba (2012) paper also comes up with similar findings to the latter in terms of the Nigerian SME. The null hypothesis of a random walk is once again rejected for Nigerian indices for the 2005-2009 period. It is concluded that the Nigerian stock markets are therefore weak form inefficient. In a BRICS country analysis for SME, Kiran (2019) founds South African stock markets to be weak form efficient during crisis and post-crisis periods. Pre-crisis however, SA markets are concluded to be weak form inefficient.

3.3.3 Findings in other emerging economies.

Robinson (2005) analysed price behaviour for all listed stocks of the Jamaican Stock Exchange (JSE) for the period 1992-2001. Autocorrelation and Runs tests utilized by the latter both significantly point to weak form inefficiency on the JSE. More specifically, the autocorrelation test rejected the null for randomness in about 65% of the stocks on the JSE while the null for normality was rejected for all 58 listed stocks by the runs test (Robinson, 2005). Filis (2006) used similar tests for a study between 2000 to 2002 for the Athens Stock Exchange (ASE) and found mixed results skewed more towards inefficiency. The runs test indicated no efficiency in the first year and efficiency in the second year analysed. This is noted to be a sign of improving efficiency over time. Adding on, the unit root test indicated that the residuals for the FTSE/ASE 20 index series were white noise thus evidence of following the random walk. On the other hand, the GARCH effects on the FTSE/ASE 20 index returns indicated volatility clustering hence inefficiency (Filis, 2006).

Furthermore, Kiran (2019) made use of variance ratio tests to check for SME in the BRICS countries between 1997 and 2018. Brazil was highlighted to have weak form efficient markets in all periods of study under the variance ratio test. For Russia, the same test indicated that weak form efficiency was present only during the crisis and post-crisis periods but not during pre-crisis periods (Kiran, 2019). These findings are consistent with another BRICS SME study by Chang, Cheng and Wang (2010). Non-linear tests however showed overwhelming evidence rejecting the random walk for all the BRICS countries (Kiran, 2019). Adding on, the efficiency of the Karachi Stock Exchange (KSE) was tested by Rabbani, Kamal and Salim (2013) over a 12-year period (1999-2010). Overall, the latter concluded that the KSE was weak form efficient. However, a closer look at the tests conducted shows that weak form efficiency is actually present for some of the subgroups of the study as shown by the runs test (Rabbani, Kamal and Sakim, 2013). These inconsistencies could be as a result of thin trading as explained by Mustafa and Nishat (2007) who found that the KSE was actually weak form efficient between 1991 and 2003 after thin trading adjustments.

3.4 Evidence of the effects of liquidity and liquidity shocks on the Stock Market.

Chapter 2 outlined relationships studied in literature shared by liquidity, liquidity shocks and the variables of the stock market such as returns, volatility and efficiency. This section of the research now seeks to uncover existing empirical evidence of such relationships across different stock markets.

3.4.1 *Findings on the relationship between Liquidity, SME and the stock market variables (prices, volatility and returns).*

Tetlock (2007) highlights that it can be challenging to accurately estimate the relationship between liquidity and efficiency using traditional financial market data. However, the latter goes on to measure liquidity using the quoted bid-ask spread and realised bid-ask spread and concluded that liquid stocks overprice low-probability events and under-price high-probability events. It is therefore noted here that liquidity can actually indicate significant noise trading and thus inhibit informational efficiency. Another study by Chordia, Roll and Subrahmanyam (2008) made use of variance ratio tests and the short-predictability order flows to proxy SME and its relation to liquidity during the 1993 to 2002 period. Variance ratio tests from this study suggested that in the more liquid regimes, the stock price series of the NYSE was closer to the random walk expectations. Overall, it was concluded that the incorporation of private information was more prevalent on the NYSE during periods of high liquidity (Chordia, Roll and Subrahmanyam, 2008). The main conclusion from the latter is that liquidity increases arbitrage activity which in turn improves SME.

Chung and Hrazdil (2010), extend and confirm the findings of Chordia, Roll and Subrahmanyam (2008) (CRS) by using a larger sample of about 4000 NYSE firms. The relationship between liquidity and SME is then tested during periods of new information using similar methods as CRS. It was concluded that new information is better absorbed into stock prices during high liquidity regimes (Chung and Hrazdil, 2010). However, the latter warns that misleading results could be given due to different portfolio sizes, trading frequencies and market capitalizations. A paper by Smith (2008) investigated the liquidity and efficiency of the African Stock markets and found that indeed SME was an important factor in improving efficiency. The latter showed that as stock market liquidity improved in South Africa, Egypt, Tunisia and Nigeria, between 2000 and 2006 their return indices became more aligned with the martingale hypothesis. The exception here was Zimbabwe whose markets were highly liquid but found to be inefficient due to economic turmoil and redundant trading systems. More evidence is found in the Thai stock market where Bariviera (2011) makes use of non-parametric measures to test the relationship between liquidity and efficiency. The findings from this analysis note that efficiency marginally responded to liquidity and did not vary with market capitalisation.

Amihud and Mendelson (1986) initiate the research on liquidity and stock returns with some ground breaking evidence. The latter modelled stock returns as an upward function of spread and confirmed this assertion showing that the two variables share a positive relationship. It was found that for the NYSE stocks between 1961 to 1980, a 1% increase in the spread would be followed by about a 0,2% increase in the risk-adjusted returns (Amihud and Mendelson, 1986). This is in line with theories discussed in Chapter 2 indicating that investors would require a premium on illiquid stocks hence an inverse relationship between liquidity and returns or rather as noted in the findings a direct relationship with spread. A recent similar study was conducted by Nayaran and Zheng (2011) on Chinese stock market liquidity using trading volume, the turnover rate and the trading probability. The overall conclusion noted that liquidity shared a negative relationship with returns on both the Shanghai and Shenzhen stock exchanges. More specifically, it was noted that in the period of study (1997-2003) only the turnover rate proxy showed a statistically significant negative relationship with the returns on both exchanges tested.

Furthermore, Marozva (2011) also investigated the relationship between stock illiquidity and returns on the Johannesburg Stock Exchange (JSE). Findings here noted that liquidity was indeed important in pricing returns on the JSE, and that illiquidity was significantly positively related to stock excess returns. Another study on the NYSE conducted by Baradarannia and Peat (2013) also investigated liquidity and expected returns. It was found that expected returns increased with stock market illiquidity for the whole sample period (1926-2008). Further analysis showed that illiquidity had significant explanatory power on expected returns post 1963 but not before that. In the Tunisian stock market, Loukil, Zayani and Omri (2010) discover significant evidence indicating that a positive premium existed for company stocks with a high price impact and low trading frequency (illiquid stocks). Another important finding in this regard is that the impact of liquidity on the premium was seasonal (Loukil, Zayani and Omri, 2010).

3.4.2 Findings on Liquidity shocks and the stock market variables (prices, volatility and returns)

The prime agenda of this research is to analyse liquidity shocks and efficiency, as such this section attempts to uncover existing evidence of how liquidity shocks interact with stock market variables. Note here that no direct evidence was found between liquidity shocks and stock market efficiency, only inferences based on the other closely related variables as discussed below. Given the scarcity of research on the subject, one of the earliest studies around the time of the global financial crisis is a study on broad money liquidity shocks and real estate prices. Adalid and Detken (2007) note that during boom periods, one of the driving forces behind real estate prices is significantly found to be broad money liquidity shocks. However, the predictive power of liquidity shocks in normal times shifts from real estate prices to consumer inflation. This analysis gave way to more findings in the stock market discussed below.

Nneji (2015) conducted a similar study using the robust regime-switching model to test the relationship between stock market liquidity shocks and stock bubbles. The latter found that stock market liquidity shocks have a much more significant impact on stock bubbles than funding liquidity shocks. Furthermore, it is highlighted that at the 10% level of significance, all sectors tested except consumer services and telecommunications show that negative stock market liquidity shocks impact stock market returns and speculative bubbles (Nneji, 2015). Most important to this study is the unwavering conclusion that the liquidity shock bubble relationship is significant over time. Albuquerque, Song and Yao (2020) made use of the tick size pilot program to investigate the price effects of liquidity shocks. The highlight of the findings in this study is that changes in transaction costs (liquidity shocks) actually account for very little for the relevant stock price change incurred.

More so, the predictive power of stock market liquidity shocks is brought to light by Bali *et al* (2014) who found that liquidity shocks predict future stock returns up to 6 months in the US. Adding on, further results from the latter showed that the significantly positive relationship between stock market liquidity shocks and future stock returns would therefore entail that negative liquidity shocks would be met by lower future stock returns (Bali *et al*, 2014). This is also confirmed by Iwananga and Hirose (2022) on the Japanese stock market when they found that higher future returns were related to positive liquidity shock. The latter reveal that such results stemmed from underreaction by market participants to liquidity shocks also explained by Jang (2021). Adding on, a South Korean stock market study by Jang (2021) agreed with the predictive nature of liquidity shocks on stock returns. However, the latter adds that for the South Korean market, the return continuation would be short lived (about 2 months as opposed to the 6 months found in the US) after a liquidity shock. It is also added that the predictive power of liquidity shocks is more significant for illiquid stocks (Jang, 2021).

Han and Huang (2022) make reference to Bali *et al* (2014) in their investigation of liquidity shocks and firm fundamentals. The results in this study explained the predictive power of liquidity shocks on stock returns as being a function of investor anticipation and reactions to future firm fundamentals. It was therefore found that firms with positive liquidity shocks exhibit better future firm fundamentals (Han and Huang, 2022). This can be argued to improve individual stock efficiency and eventually spill over to overall stock market efficiency. The robustness checks indicate a highly significant coefficient of liquidity shocks giving further legitimacy to these findings. From the EMH covered in Chapter 2, the predictability of stock returns by liquidity shocks highlighted in this section can be said to dampen stock market efficiency since investors would now be able to beat the market. This is proved by Bali *et a*l (2014) who found that a portfolio sorted by observing liquidity shock movement would be able to earn significantly above-average returns of about 0,7% to 1,2% per month. Furthermore, when it comes to stock market volatility, Ma *et al* (2018) find that liquidity shocks act as a channel through which volatility affects international market stock returns also affecting overall efficiency.

3.5 Evidence on the use and effectiveness of liquidity measures.

In this section the aim is to find evidence on the performance and mechanics of the Amihud, bid ask spread and trading volume measures of liquidity. As the selected measures for this research, it is fundamental to understand how well they perform against other measures and if indeed they best serve the research goals.

3.5.1 Findings on the Amihud (2002) illiquidity measure.

Goyenko, Holden and Tizcinka (2009) test the performance of price impact (liquidity) measures in a horse races analysis. It was found that the Amihud (2002) illiquidity measure came out at the top against the Amivest and other price impact measures. More specifically, the Amivest price impact measure was actually deemed ineffective. However, Goyenko, Holden and Tizcinka (2009) indicate that all price impact measures failed to capture the cross-sectional static price impact component. Adding on, another study by Brennan, Huh and Subrahmanyam (2013) investigates the Amihud illiquidity premium. An important finding by the latter notes that the Amihud (2002) measure performs better when turnover is used as opposed to dollar trading volume. In contrast to this, however, Lou and Shu (2017) highlight that the Amihud (2002) measure is actually driven by the trading volume component. Furthermore, when it comes to an illiquidity premium, Brennan, Huh and Subrahmanyam

(2013) decompose the Amihud measure and find that only the negative day element is responsible for a return premium.

Adding on, Bedowska-Sojika, Echaust and Just (2022) provide similar results to the latter as they test the asymmetry of the Amihud proxy in the case of positive and negative returns using the Block Maxima method. The paper explores extreme illiquidity for European stock markets and finds that clustering of extreme volatility was more significant for negative returns than positive returns in emerging stock markets as shown by the Amihud (2002) measure. The overall conclusion here is that the Amihud illiquidity proxy verified the asymmetry in extreme illiquidity market conditions. More so, Coen and de La Bruslerie (2019) find that the Amihud (2002) measure significantly determines abnormal returns after mergers and acquisitions. Here the empirical results of the latter show that the Amihud measure was statistically significant and negative when explaining the abnormal returns. Additionally, another finding highlighted a significant influence by the Amihud measure on financial analyst's behaviour and more specifically on how they modify their forecasts. Another interesting find by Coen and de La Bruslerie (2019) notes that the price informativeness was actually well proxied by the Amihud measure.

3.5.2 Findings on the bid ask spread measure.

Some of the earliest findings on bid ask spread (spread) are given by Amihud and Mendelson (1986). The latter found that NYSE spreads from 1961-1980 share a negative relationship with firm size and a positive relationship with stock returns. Another early study by Atkins and Dyl (1990) indicates that the highest abnormal returns were associated with the widest spreads. It is also noted that although the relationship between abnormal returns and the spread is significant, the adjusted r squared from the OLS regressions were very low. This entails that changes in abnormal returns were not primarily caused by changes in the spread (Atkins and Dyl, 1990). Note here that the findings here are in line with the discussions in Chapter 2.

Furthermore, Cai, Hudson and Keasey (2004) investigate intraday spread behaviour on the London Stock Exchange. Findings from this paper indicate that the intraday spreads exhibit a reverse J shape pattern entailing wide spreads at open and narrow spreads at close of the market. A similar study by Abhynkar, Ghosh and Limmack (1997) partly agrees with the latter noting that spreads were wide at open and close thus a U shape pattern. Adding on, Gwilym and Thomas (2002) conduct a performance analysis of quoted and implied spreads on the FTSE

100 futures market. One of the main findings from this paper was that accurate spreads can effectively be used to measure market efficiency.

3.5.3 Findings on the trading volume measure.

Cai, Hudson and Keasey (2004) found that trading volume exhibits a two-hump pattern in their intraday analysis. More specifically, evidence shows that trading volume was actually not at its highest during the opening and closing of a market. Abhynkar, Ghosh and Limmack (2003) also add that trading volume varies depending on the level of liquidity in the market. The Karpoff (1987) paper gives clearer findings on the relationship between trading volume and stock prices. The latter cited empirical analysis that emphasises a 'positive volume-absolute price change correlation'. Evidence here showed that in stock markets, trading volume associated with price increases is greater than trading volume associated with price falls (Karpoff, 1987). Another interesting finding was centred around the link between trading volume and volatility. Here, Girard and Biswas (2007) found that emerging stock markets were highly sensitive to unexpected volume changes and large information shocks. A negative relationship is found to exist between expected trading volume changes and volatility which was noted to increase the likelihood of inefficiency (Girard and Biswas, 2007). All the above findings generally agree that trading volume is not complex to measure or interpret thus less chances of reporting inaccurate results.

3.6 Chapter Summary.

The chapter managed to provide empirical evidence on efficiency in both developed and developing stock markets. The main findings here were that efficiency has significantly improved in both developing and developed markets following the advancement of trading technology and systems. There is a relative consensus that most developed stock markets are weak form efficient with the exception of the Tokyo Stock Exchange found to have not improved significantly over time (Nagayasu, 2003). The results in developing stock markets were mixed with only a handful being found to be efficient consistently (Botswana, China, Côte d'Ivoire, Kenya, Mauritius, South Africa and Tunisia). The presence of SME in South Africa shown here allows the research to carry on and thus test the impact of liquidity shocks on South African stock market efficiency to be determined in Chapter 5.

More so, evidence on the impact of liquidity and liquidity shocks on stock market variables was also covered in this section. The highlights of the findings were that liquidity improves stock market efficiency. It is also noted that there exists a positive relationship between stock illiquidity and stock returns due to the illiquidity premium demanded by investors (Amihud and Mendelson, 1986). The results on liquidity shock interactions with the stock market revealed the following: (i) Liquidity shocks influence and predict stock market price bubbles. (ii) Liquidity shocks share a positive relationship with stock market returns. Note here again that empirical evidence has left a gap on the direct effect of liquidity shocks on SME. Therefore, more emphasis as to why it is important for this research to conduct an empirical analysis on liquidity shocks and stock market efficiency.

Section 3.5 looked at the evidence surrounding the liquidity measures chosen for the research. For the Amihud (2002) measure, the main takeaways were that it can be considered the best measure of price impact. However, it is still debatable whether it performs better when the turnover ratio is used or the dollar trading volume. It was also shown that the Amihud (2002) measure can be an adequate proxy for price informativeness and also determines abnormal returns after mergers and acquisitions. Evidence on the bid ask spread revealed a positive and significant relationship with stock returns. More interestingly, overwhelming evidence also agreed that intraday spreads exhibited a reverse J pattern. The trading volume was found to show a two-hump pattern in an intraday study by Cai, Hudson and Keasey (2004). Lastly, trading volume is greater when stock prices are increasing than when they are falling.

CHAPTER 4

DATA AND METHODOLOGY.

4.1 Introduction.

As indicated in Section 1.3, the goal of the research is to investigate how liquidity shocks impact capital market efficiency in South Africa. This Chapter now discusses all the approaches taken to address the goals and sub goals of the study. The research paradigms are covered first in section 4.2 with more emphasis on post-positivism. Next, the research design ensues in section 4.3 covering the theoretical framework, definition of variables, explanations of data and econometric techniques. Lastly, the causality tests are also be discussed.

4.2 Research Paradigms.

According to Baker (2021), research paradigms can be described as ideals and beliefs held by scholars that influence the manner in which they conduct a study. In agreement with the latter, Kivunja and Kuyini (2017) add that research paradigms can be better understood as a researcher's “worldview” influencing their thought process concerning the meaning and interpretation of research findings. Note here that the elements of any paradigm include epistemology, ontology, methodology and axiology. We mainly focus on the methodology which speaks to the research design, and procedures used to answer the problem statement and research goals. Baker (2021) and Kivunja and Kuyini (2017) all agree that the most prominent paradigms include the positivist, interpretivist, critical, pragmatic and constructivist paradigm. This research will employ a balanced combination of positivism and interpretivism better known as post -positivism.

The post-positivist paradigm came to be as a revolt against the rigidities of positivism such as ignoring context and thus generalising results and, completely separating the researcher from the research such that researcher bias would be ruled out (Fox, 2008). Baker (2021) defines post-positivism as an approach where reality is expansive, researcher bias is acknowledged, and findings cannot be generalised given the varied contexts. Panhwar, Ansari and Shah (2017) note that post-positivism welcomes the use of multiple methods to analyse a research problem and thus achieve objective results with minimum bias. Note here again that this research makes use of the post-positivist paradigm in a quantitative explanatory framework. This is because to measure liquidity, three approaches are be utilised taking into account three different contexts, namely the resource, financial and industrial stock market sectors. Mathematical and econometric techniques are be employed to answer the research goals and also confirm or debunk some of the theories discussed in Chapter 2 and the hypothesis outlined in Section 1.4.

4.3 Research Design.

4.3.1 Data Sources.

For this quantitative research, the main sources of data are the Thomson Reuters DataStream (2022) and IRESS (2022). The sample period of study is 10 years although the data covers the period starting 03 January 2011 to 31 December 2021 to cater for the rolling window method used to calculate the average illiquidity outlined below. Daily stock prices, volume and turnover data was sourced from four different indices namely the Financial Times Stock Exchange/ Johannesburg Stock Exchange (FTSE/JSE) SA All Share, FTSE/JSE SA Industrial 25, FTSE/JSE SA Resource 20, and FTSE/JSE SA Financial 15. Additionally, the United States of America dollar to South African Rand (USD/ ZAR) exchange rate data used as a control variable was collected for the same sample period, and also acquired from Thomson Reuters DataStream (2022). Stock market capitalisation data for the research was acquired from IRESS. Regression variables shall thus be mathematically computed from the data collected here.

4.3.2 Theoretical Framework/ Conceptual Framework.

In Chapters 2 and 3, the research discussed theories, literature and empirical studies regarding the relationship between liquidity, liquidity shocks and stock market efficiency. At this juncture, the research now partially adopts existing models to measure illiquidity shocks found in Bali *et al* (2014), Ma *et al* (2018) and Jang (2022) since no identical research exists. This empirical analysis is utilised to tackle the goals of the research.

4.3.2.1 Model Specification.

For sub-goal 1, the research utilises a time series Autoregressive Distributed Lag model (ARDL) similar to the one conducted by Nazima (2011). In the same light, for sub-goal 2, the research employs a panel ARDL in line with Humpe and McMilan (2020). Nazima (2011) and Humpe and McMilan (2020) investigate exchange rate volatility to changes in foreign direct investment and the relationship between macroeconomic variables and the exchange rate respectively. By employing aspects from both latter methods, this research specifies two main equations as seen below. The dependent variable, stock market efficiency is proxied by the stock market turnover ratio. Independent variables include the Amihud illiquidity shock and the change in turnover liquidity shock. More so, three control variables namely the USD/ZAR spot exchange rate, conditional volatility proxied by the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model residuals, and the trading volume are used. We therefore specify the following equations.

$$SMTURN_t = \beta_0 + \beta_1 LIQUISHOCK_t + \beta_2 EXCH_t + \beta_3 VOLA_t + \beta_4 VOLU_t + \mu_t \text{ ………. } (4.1)$$

Equation 4.1 above estimates the relationship between stock market efficiency proxied by the stock market turnover ratio (*SMTURN*) and the ***Amihud*** illiquidity shock (*LIQUISHOCK*). Where the control variables exchange rate, volatility (conditional volatility) and trading volume are depicted as *EXCH, VOLA* and *VOLU* respectively. Adding on, the variables $\beta 0$ represent the intercept while μ represents the error term.

$$SMTURN_t = \beta_0 + \beta_1 \Delta TURNSHOCK_t + \beta_2 EXCH_t + \beta_3 VOLA_t + \beta_4 VOLU_t + \mu_t \text{…….. } (4.2)$$

Equation 4.2 above is a slight variation of 4.1. This equation estimates the relationship between stock market efficiency and the ***turnover*** liquidity shock. Here the liquidity shock is now measured by changes in turnover depicted as *ΔTURNSHOCK*. All other variables remain the same. Note also that for sub goal two, these two equations are run through a panel ARDL, and cross-sectional results extracted from EViews to analyse the impact of liquidity shocks in each of the three industries mentioned earlier. Hence the use of the panel ARDL model. Results here are be met by two contesting priori expectations outlined in the empirical findings Chapter 3: first, positive liquidity shocks improve firm fundamentals and hence increase individual stock efficiency which ultimately improves stock market efficiency (SME), second, the basis that liquidity shocks predict future stock market returns and thus in a way undercut the principles of efficiency outlined by the EMH of not beating the market.

Lastly, the research ran Vector Autoregressive tests for each sub goal to analyse the impulse response (speed of adjustment in the short and long run after liquidity shocks to stock market efficiency) and the decomposition analysis to indicate how long the liquidity shocks last. Priori of expectations here from Bali *et al* (2014) and Jang (2021) tells us that liquidity shocks on stock market returns last between 2 to 6 months. As such it is reasonable to expect little to no deviation in the case of SME.

4.3.3 Definition of variables.

This section shows how the variables to be used in the econometric techniques described in Section 4.3.4 are derived and the reasoning behind their selection for this research.

4.3.3.1 Stock Market Turnover Ratio.

As stated earlier on in the Chapter, the stock market turnover ratio serves as the dependent variable and proxies stock market efficiency. This measure indicates how active and thus efficient domestic stock markets are and thus can be compared relative to other stock markets. Note here that the World Bank (2016) lists the stock market turnover ratio as a go-to proxy for financial market efficiency hence its use in this research. According to The Global Economy (2022), data collected between 1975-2020, it was noted that South Africa ranked 24th with a stock market turnover ratio of 27,94. This research therefore calculates the measure as follows.

$$SMTURN_t = \frac{Trading\ Volume}{Stock\ Market\ Capitalisation} \qquad (4.3)$$

Daily trading volume data was collected from the Thomson Reuters DataStream (2022) while stock market capitalisation data collected from IRESS (2022).

4.3.3.2 The Amihud liquidity Shock.

Following the approach by Bali et al (2014) and Jang (2021), we define liquidity shocks for an entire index on a daily basis and not individual stocks as done by the latter. As such, the Amihud illiquidity shock here is defined as the difference between daily liquidity on the index and its average over the last year (12 months). The daily illiquidity on the index follows Amihud's (2002) approach, as a price impact and thus illiquidity measure and is calculated as follows.

$$ILLIQ_t = \frac{\%\,price\ change * Volume}{Log\ \ Volume} \qquad (4.4)$$

Where ILLIQ is the daily illiquidity on the index. The illiquidity shock is thus calculated from the latter as the inverse sign of the difference between *ILLIQ* and its average over the last 12 months as follows (Jang, 2021).

$$LIQUISHOCK_t = -(ILLIQ_t - AVGILLIQ_{t-12,t-1}) \quad (4.5)$$

Where *AVGILLIQ* is as stated before, the average *ILLIQ* measure over a year. As such, based on equation 4,5, a positive *LIQUISHOCK* entails that a stock has become more liquid than it was over the last year (Jang, 2021). In other words, liquidity would have increased relative to the last 12 months. Since *LIQUISHOCK* is calculated from illiquidity, it behaves in the opposite manner to the Change in Turnover shock explained below. As such note that *LIQUISHOCK* entails illiquidity shocks in this paper.

4.3.3.3 Change in Turnover Shock measure.

The stock market turnover is one of the least complex measures utilised by this research. The stock market turnover is a readily available indicator of stock market liquidity. To measure the liquidity shock from daily turnover, the inter day change as (Today turnover – Yesterday turnover) is firstly calculated. This gives the second liquidity shock measure ΔTURNSHOCK. Note that the latter unlike LIQUISHOCK directly measures liquidity shocks. Although the stock market turnover is be readily available from the Thomson Reuters DataStream (2022), note here that it is calculated as follows.

$$Turnover = \frac{Total\ Number\ of\ Shares\ Traded}{The\ Average\ number\ of\ outstanding\ Shares} \quad (4.6)$$

4.3.3.4 The Exchange Rate.

The exchange rate defined as the value of one currency in terms of another is our first control variable in equations 4.1. and 4.2 specified above. The use of the exchange rate in this research is influenced by its impact on the domestic stock market including facilitating the interactions with international stock markets and investors. Here we make use of the USD/ZAR spot rate data collected from Thomson Reuters DataStream (2022). Note that the USD is used as a base currency here due to its function as the official reserve currency world over.

4.3.3.5 Conditional Volatility (proxied by GARCH residuals)

The previous Chapters revealed what crucial role volatility plays when it comes to both liquidity shocks and stock market efficiency. It is thus important for this research to include volatility as a control variable. Brooks (2014) highlights modelling volatility of a times series as one of the major uses of the GARCH model in Financial Economics. We employ the residuals estimated from the GARCH model as our proxy for conditional volatility (*VOLA*) in equation 4.1 and 4.2. The mechanics of the GARCH model are discussed in Section 4.3.4 below. Note that a GARCH model is applied after testing for ARCH effects.

4.3.3.6 Volume Traded.

As with stock turnover, the volume of stocks traded is also an easy measure to decipher. This variable reflects the total quantity of stocks traded belonging to a particular index in a given period of time. The volume traded is the third control variable in the models specified by the research. It can also be regarded as a stock market liquidity proxy.

4.3.4 Econometric techniques.

4.3.4.1 Autoregressive Conditional Heteroskedastic (ARCH).

Given the usual heteroskedastic nature of variance errors in financial data, it becomes more appropriate to utilise nonlinear models such as the ARCH model. For this research to extract the volatility of stock returns and thus make use of the GARCH model, the prelude is to test for ARCH effects detected using the Engle (1982) test (Brooks, 2014). Another motivation for employing the 'ARCH family' of models in this research is a financial time series data phenomenon known as volatility clustering. Note here that this is yet another check list item to be present before proceeding to a GARCH. According to Brooks (2014), volatility clustering speaks to how large stock price changes are followed by larger changes and small price changes also followed by smaller changes. On figure 4.1, one can observe volatility clustering between 2007 to late 2009. Due to the international financial crisis of 2009, the data shows extreme positive and negative returns in a short period of time. This here is another lens to understand the point of this research given that the reason for volatility clustering is stated to be high frequency arrival of data all at the same time rather than evenly spaced throughout time periods. To test for ARCH effects, the squared residuals on p number of lags specified by the researcher are regressed. The null hypothesis is that all p lags of residuals do not have coefficients different from zero. Consider the ARCH (1) model specified below adopted from Brooks (2014).

$$y_t = \beta_1 + \beta_{2x2t} + \beta_{3x3t} + \beta_{4x4t} + \mu_t \ldots\ldots \quad (4.7)$$

Equation 4.7 above is a linear regression run to extract the residuals to formulate the (ARCH (1)) squared residuals equation specified below.

$$\alpha_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + v_t \ldots\ldots \quad (4.8)$$

Where v_t is an error term normally distributed with a unit variance and zero mean, u_t^2 is the squared residuals also distributed normally with a zero mean.

An illustration of volatility clustering is shown below.

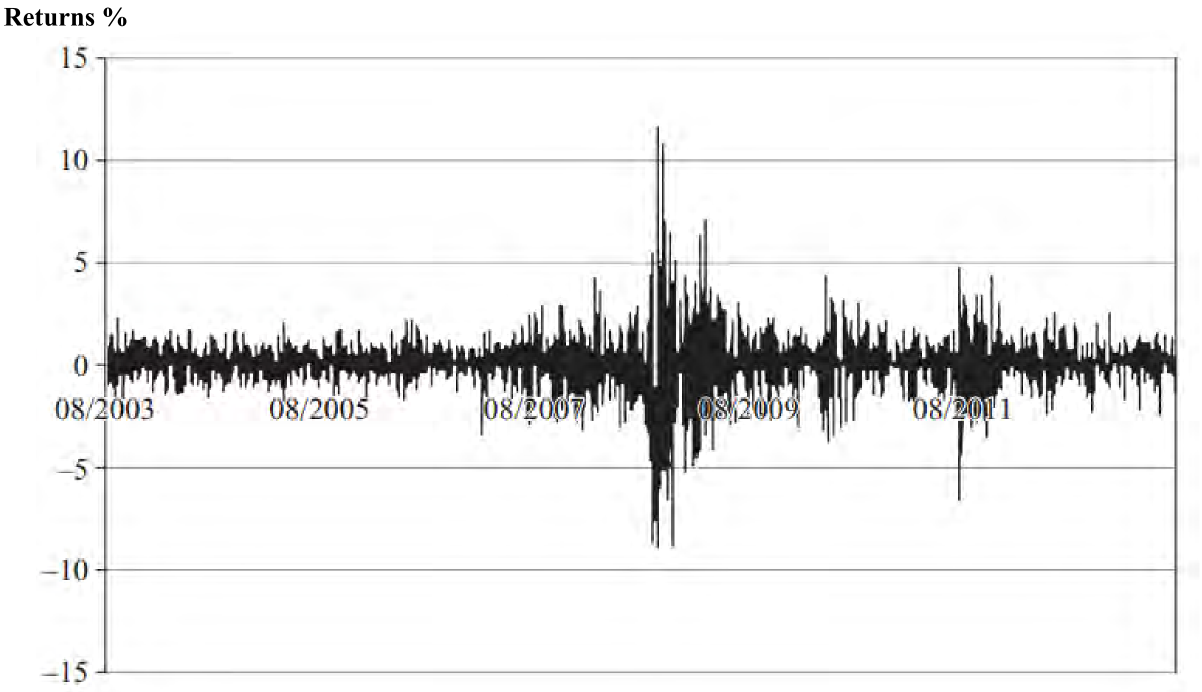

Figure 4. 1 Daily returns for the S&P 500 index for 2003-2013.

Source: Brooks (2014)

4.3.4.2 Generalised Autoregressive Conditional Heteroskedasticity (GARCH model).

Developed by Bollerslev (1986) and Taylor (1986) the GARCH model has become more accepted than the ARCH model due to its parsimony and aversion to overfitting (Brooks, 2014). For the GARCH model, the Ordinary Least Squares method is abandoned, and the maximum likelihood technique picked up and from it the Log-likelihood function is formed. The latter method is very effective in finding parameters both linear and nonlinear. In its simplest form the GARCH (1,1) is estimated as follows (Brooks, 2014),

$$\sigma_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \ldots\ldots \quad (4.9)$$

Here it can be noted that the GARCH model is simply a variation of the ARCH model which accommodates an infinite number of squared error terms and conditional variance terms. To extend the model, simply state it as a GARCH (p, q), where p is the lags of conditional variance terms and q is the number of squared error terms. Consider the equation below,

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \ldots + \beta_p \sigma_{t-p}^2 \ldots\ldots\ldots\ldots\ldots \quad (4.10)$$

Although the extended model is an option, as a general rule of thumb, the GARCH (1,1) is considered sufficient to model volatility and thus capture volatility clustering (Brooks, 2014). As such, this research employs the GARCH (1,1) to extract the volatility of the FTSE/JSE All Share, Financial 15, Resource 20 and Industrial 25 indices.

4.3.4.3 Vector Autoregressive Modelling (VARs). (Variance decomposition and impulse responses)

The VAR model was introduced by Sims (1980). Brooks (2014) defines a VAR model as a systems regression model meaning that more than one dependent variable could exist. From another perspective, a VAR can also be seen as an alternative to large scale simultaneous equations. More so, Shrestha and Bhatta (2018) highlight that the VAR model mechanism allows for reverse causality tests of both independent and dependent regressions making use of their own past values. Additionally, VARs also assume that all regressions are endogenous. Consider the following simple form VAR equations testing for the relationship between *SMTURN* and *LIQUISHOCK* in this research,

$$SMTURN_t = \delta_1 + \beta_{11} LIQUISHOCK_{t-1} + \beta_{12} SMTURN_{t-1} + \mu_{1t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.11)$$

$$LIQUISHOCK_t = \delta_2 + \beta_{21} SMTURN_{t-1} + B_{22} LIQUISHOCK_{t-1} + \mu_{2t} \ldots\ldots\ldots\ldots\ldots\ldots \quad (4.12)$$

Where μ_{1t} and μ_{2t} are uncorrelated white noise disturbance terms. It is also important to choose the appropriate lag length when using VARs. This research makes use of the Akaike Information Criterion (AIC) to select an adequate lag length. Note here that our application of the VAR in this research is to understand the nature of the relationship between *SMTURN* and the two liquidity shocks measured *LIQUISHOCK* and *ΔTURNSHOCK*. As such, the VARs impulse response and variance decompositions which form part of block F tests are utilised (Brooks, 2014).

According to Brooks (2014), VAR impulse responses trace the shocks for each variable in the VAR equation separately. In essence, it reveals how the dependent variables in a VAR model reacts to shocks applied to the system. On the other hand, the variance decompositions which offer similar information to the latter produces the proportion of movements in the dependent variable as a result of their own shocks against shocks to other variables (Brooks, 2014). This research therefore utilises both methods to investigate the duration of liquidity shocks on stock market efficiency and how quickly these shocks impact SME. Adding on, the research employs the orthogonalized impulse responses to circumvent the ordering variables problem.

4.3.4.4 Determining the stationarity of research variables.

Before the variables explained above are utilised for any econometric processes, stationarity tests are conducted to decipher the order of integration for each one. Although the ARDL model can deal with times series of different orders (order two and above excluded), the research still conducts stationarity tests to avoid any spurious regressions affecting the results. Since this research runs a time series and panel ARDL, separate tests are conducted for the time series data and the panel data. According to Brooks (2014), a stationary time series can be defined as that which has a constant mean, variance and covariance. In other words, the times series will be mean reverting over time. Brooks (2014) also notes that a stochastic process with such properties can be referred to as a white noise process. Here it is discovered that a random walk model without drift also takes the same mean reverting processes and can be mathematically depicted as follows.

$$Y_t = \rho(Y_{t-1} + U_t) \quad (4.13)$$

Where $-1 \leq \rho \leq 1$. ρ is the correlation coefficient, U_t is the white noise error term and Y_t is a random walk (Mulamu, 2021). Note that in the case where $\rho = 1$, then a random walk with drift would be the result and a unit root would also be present otherwise if $|\rho| \leq 1$ then time series Y_t would be regarded stationary.

As might have already been noted, the unit root is a statistical procedure used to determine stationarity in a time series. Shrettha and Bhatta (2018) highlight three main methods used to test for time series data stationarity and thus the unit root namely the Augmented Dickey Fuller, Phillips Perron (PP) and KPSS tests. The Augmented Dickey Fuller (ADF) test is the most common of these and are thus be utilised by this research using the EViews software to run the tests. The ADF can therefore be mathematically modelled as follows as adapted from Shrettha and Bhatta (2018),

$$\Delta y_t = \mu + \delta y_{t-1} + \Sigma_{i=1}^{k} \beta_1 \Delta y_{t-i} + e_t \quad (4.14)$$

Where $\delta = \alpha - 1$ and $\alpha = the\,coefficient\,of\,y_{t-1}$. $\Delta y_t =$ the first difference of y_t specifically $y_t - y_{t-1}$. The null hypothesis of the ADF is that the time series is not stationary or has a unit root therefore rejecting the null would entail those times series is stationary. This method is used to decipher the order of integration of all the variables defined above. Our priori of expectation is that most variables will be at most integrated of level 1 given that we are working with stock data. The PP tests follows the same hypothesis and processed as the ADF. These tests are used to determine the JSE All Share time series data stationarity.

The panel data stationarity is determined using panel unit root tests. These include the LLC, IPS and ADF Chi-Square tests explained by Levin et al (2002), Im et al (2003) and Maddala and Wu (1999) respectively.

4.3.4.5 Cointegration Tests.

The research also conducts cointegration tests developed by Granger (1981) and improved by Engle and Granger (1987) between the stock market turnover ratio, and liquidity shocks proxied by the Amihud liquidity shock and changes in turnover. For this research, these are embedded in the ARDL mentioned below and help understand the long-term relationships between the two variables. Note here that the bounds test is applicable to the time series ARDL results but not the panel ARDL results. This is because there is no bounds test approach for a panel ARDL as a system. As highlighted by Shrettha and Bhatta (2018), cointegration is present when two variables share a long-term relationship. The logic here is that one variable pulls the other over time such that both variables end up sharing the same movement over time. Another way to put it is that if the linear combination of in our case the stock market turnover ratio and the Amihud liquidity shock are stationary, then the variables are cointegrated (Brooks, 2014). In actual fact, it is the residuals of the linear combination of variables that are tested for stationarity in this case. Therefore, if cointegrated, the understanding is that the residuals of these variables will have a constant mean thus stay close together over time and not wander apart.

4.3.4.5.1 The Autoregressive Distributed Lag Model (ARDL)

As stated earlier, the research employs both a time series and panel ARDL to identify any long run relationships from the variables stated above. This is especially a crucial component when dealing with stock market data which tends to be intertwined one way or another. Note here that the ARDL is a combination of two equations at its core. The first being the dependent variable and lags of itself, followed by the independent variables and their own lags as well.

Some of the advantages of using the ARDL over other models include its ability to produce consistent estimates of the long-run coefficients (Perisan and Shin, 1995). The latter also indicated that the ARDL provides flexibility which allows for estimation even if the variables are integrated of different orders, I (0) and I (1) for example. In agreement to this, Nkoro and Uko (2016) highlight that when using the ARDL, pre-tests and unit root tests are not a necessity. However, since the model may crash in the presence of an I (2) integrated stochastic trend, unit root tests are done as a precaution.

The F-Statistic (Wald Test) is utilised to detect long-run relationships of the underlying variables. Here, a long run relationship would be detected in the event that the F-Statistic is greater than the critical values (Nkoro and Uko, 2016). It is also important to highlight that the ARDL method was regarded as adequate to correct the problem of endogenous regressors and serial correlation by Perasan and Perasan (1997). With that in mind, the research therefore adopts the time series ARDL specification adopted from Parasan and Shin (1995) which was described as ARDL (p,q,......,q).

$$SMTURN_t = \beta_0 + \Sigma_{j=1}^{p} \beta_j SMTURN_{t-j} + \Sigma_{j=0}^{a} \beta_j X_{t-j} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.15)$$

Where *SMTURN* the stock market turnover ratio is our dependent variable, *X* is a (4x1) vector of explanatory variables and μ is the error term. The research therefore uses equation (4.16) to verify the relationship between stock market efficiency (SMTURN) and liquidity shocks on the JSE All Share index.

For the panel ARDL estimation, this research uses the Pooled Mean Group (PMG) model introduced by Perisan, Shin and Smith (1999). The PMG is considered an intermediate approach when compared to the Dynamic Fixed Model (DFE) and the Mean Group model (MG) since it binds long run coefficients to be the same but short run coefficients and error variances are allowed to differ. It can then be noted that dynamic specification is allowed by the PMG model since short run coefficients are heterogenous. On the other hand, homogenous long run coefficients make the PMG consistent and efficient (Perisan, Shin and Smith. 1999). For this research, the long run slope homogeneity is important because the panel groups (Financial 15, Resource 20, and Industrial 25 indices) face common environmental characteristics, technologies and policies of the JSE in South Africa. With that in mind, consider the following reparametrized panel ARDL estimation adopted for this research from Perisan, Shin and Smith (1999).

$$\Delta SMTURN_{it} = \sum_{k=1}^{p-1} \lambda_{ik}^{*} \Delta SMTURN_{i,t-k} + \sum_{k=0}^{q-1} \sigma_{ik}^{*1} \Delta X_{i,t-k} + \phi_i SMTURN_{i,t-1} + \beta_i X_{it} + \omega_i + \varepsilon_{it} \ldots\ldots (4.16)$$

Where λ_{ik} *and* σ_{ik} are short run coefficients, ϕ is the group specific error correction coefficient that infers the speed of adjustment and β_i is a vector of long run coefficients that infers long run causality for each regressor. The research therefore uses equation 4.8 to determine the relationship between stock market efficiency and liquidity shocks across the three industries (financial, industrial and resources indices).

4.3.4.6 Granger Causality Tests.

When many lags of variables are included in a VAR model, restrictions are applied to the model which actually liken it to causality tests (Brooks, 2014). As such, a scenario where past lags of say variable X affect current values of variable Y is what Granger (1989) developed and is thus now called Granger Causality. A precondition needed to apply the Granger causality test is that variable and X and Y should be cointegrated otherwise they are considered independent. This research seeks to further determine if past values of liquidity shocks (*LIQUISHOCK* and *ΔTURNSHOCK*) influence current values of stock market efficiency (SMTURN). The research follows the Granger causality specification by Mulamu (2021) and compute the following equations. Note that there are 4 equations here due to our two liquidity shock measures being tested.

$$lnSMTURN_t = a_0 + \Sigma_{i=1}^{k} a_i lnSMTURN_{t-i} + \Sigma_{i=1}^{k} b_i lnLIQUISHOCK_{t-i} + e_{1t} \ldots\ldots (4.17)$$

$$lnSMTURN_t = c_0 + \Sigma_{i=1}^{k} c_i lnSMTURN_{t-i} + \Sigma_{i=1}^{k} d_i ln\Delta TURNSHOCK_{t-i} + e_{2t} \ldots\ldots (4.18)$$

$$lnLIQUISHOCK_t = f_0 + \Sigma_{i=1}^{k} f_i lnSMTURN_t + \Sigma_{i=1}^{k} g_i lnLIQUISHOCK_{t-i} + e_{3t} \ldots\ldots (4.19)$$

$$ln\Delta TURNSHOCK_t = h_0 + \Sigma_{i=1}^{k} h_i lnSMTURN_t + \Sigma_{i=1}^{k} i_i ln\Delta TURNSHOCK_{t-i} + e_{4t} \ldots\ldots (4.20)$$

- Where $lnSMTURN_t, lnLIQUISHOCK_t$ *and* $\Delta TURNSHOCK_t$ are the log of the stock market turnover ratio, Amihud illiquidity shock and change in turnover liquidity shock respectively. The research thus tests the following hypotheses on the relationship between liquidity shocks and the stock market turnover ratio,
- *SMTURN* Granger causes *LIQUISHOCK*, synonymous with *SMTURN* Granger causes *Δ*TURNSHOCK. Here the past lags of stock market turnover ratio and thus would influence the current liquidity shocks but not the other way around.

- *LIQUISHOCK* Granger causes *SMTURN*, synonymous with *ΔTURNSHOCK* Granger causes *SMTURN* but not the other way round. Here the past lags of liquidity shocks would be considered to influence current values of the stock market turnover ratio and thus stock market efficiency.
- The third hypothesis is a bidirectional causality meaning that past lags of both liquidity shocks influence current values of the stock market turnover ratio and vice versa. This can also be regarded as feedback causality.
- There is no Granger causality between SMTURN and LIQUISHOCK/ ΔTURNSHOCK and vice versa. This means that the variables are independent as there is no relationship.

4.4 Chapter Summary.

This chapter outlined the data, methodology and econometric techniques which are used in the following chapter to determine the results and thus answer the research goals. Note that the methods and procedures selected have been deemed adequate by some of the empirical evidence readings covered in Chapter 3 that are closely related to this research.

CHAPTER 5

PRESENTATION AND DISCUSSION OF RESULTS

5.1 Introduction.

Making use of the methods discussed in Chapter 4, this Chapter presents the results answering the overarching goal on the relationship between liquidity shocks and stock market efficiency. The two-hypothesis tested under sub goal one and two are, do liquidity shocks impact stock market efficiency and, the variation in the impact of liquidity shocks on stock market efficiency across the financial, resource and industrial sectors of the JSE respectively. Both hypotheses are addressed under section 5.3.4. The chapter will thus be structured as follows. Firstly Section 5,2 will look at the stylised facts which analyse the trends and descriptive statistics of our data. Section 5.3 follows with the analysis of the results of all tests conducted to answer the research goals, then we conclude in Section 5.4.

5.2 Stylised Facts.

As highlighted above, this section will cover the descriptive statistics to understand the performance of each index relative to the other. The trend analysis will also help visualise the patterns followed by variables of interest in each index.

5.2.1 Descriptive Statistics.

This section unpacks the descriptive statistics of the returns on the JSE All Share, Financial 15, Industrial 25 and Resource 20 indices for the full 10-year period sample (Jan 2012-Dec 2021) and two 5-year sub periods within this sample for comparison analysis. Another reason for dividing the sample period into two is to remove the effect of any structural breaks that might have occurred which could affect the results. The descriptive statistics will also help understand the performance of each index in relation to the other indices. This will give a baseline understanding before analysing the impact of liquidity shocks and the relationships formed in this regard. Note that we make use of the following types of descriptive statistics: measures of central tendency, measures of dispersion and measures of normality.

For measures of central tendency, the focus will be on the mean and median. The mean will give us a proxy of the expected return of each index, but since it can be affected by extreme values (outliers) the median acts as a fail-safe in that regard. The standard deviation (S.D) will be used to gauge the spread of data across time around the mean. In financial economics, the standard deviation depicts volatility and therefore risk of a financial asset and in our case the risk of each index over the sample period. In terms of measures of normality, we turn to kurtosis and skewness. Kurtosis measures the combined weight of tails of a distribution in comparison to the rest of the distribution. We then define three types of kurtoses, mesokurtic, leptokurtic and platykurtic. A normal distribution is called mesokurtic with a kurtosis of three. A distribution with fatter tails than the normal distribution is called leptokurtic and has a kurtosis greater than three. Lastly, a distribution with thinner tails is known as platykurtic and has a kurtosis less than three. Skewness also measures the shape of the distribution by giving the degree of asymmetry of the computed observations. A skewness of zero is given by a symmetric distribution. Here mean = median = mode. The frequency of numbers greater or less than the mean is evenly spread. A positively skewed distribution (greater than zero) has a long tail on the right side implying that mean > median > mode. In such a distribution we have a small frequency of larger numbers greater than the mean. Conversely, a negatively skewed (less than zero) distribution has a long tail on the left implying that the mean< median< mode. Thus, in such a distribution there is a small frequency of numbers less than the mean.

Table 5. 1 Descriptive Statistics for the full period (January 2012-December 2021)

	JSE All Share	**JSE Financial (15)**	**JSE Industrial (25)**	**JSE Resource (20)**
Mean	-0.027%	-0.011%	-0.041%	0.003%
Median	-0.055%	-0.067%	-0.098%	-0.024%
Maximum	10.77%	14.19%	9.55%	16.87%
Minimum	-8.65%	-12.66%	-6.79%	-11.91%
Standard Deviation	1.06%	1.49%	1.12%	1.73%
Skewness	0.775	0.801	0.471	0.504
Kurtosis	14.42	15.59	7.722	10.62

Source: EViews output. Data from Thomson Reuters and IRESS (2022).

Table 5.1 summarises the descriptive statistics for the returns on four South African stock indices (All Share, Financial (15), Industrial (25) and Resource (20)). The mean and median values of all indices fall within a plus or minus one range from zero. This satisfies a priori expectation that stock return series do not deviate from their mean over time and thus can be concluded to be stationary at level terms (without differencing). The highest and only positive mean value of 0.003% was captured for the Resource (20) index, while the Industrial (25) index had the lowest mean returns of -0.041%. The Resource (20) index also had the highest standard deviation value of 1.73% hence aligning with both the CAPM and Markowitz theories that higher stock returns come with higher risk (Edwin *et al*, 2009). Note that the high standard deviation can also be confirmed by checking the spread between the maximum and minimum returns values. As can be seen above, the Resource (20) index has the widest spread of about 28% between its maximum (16.87%) and minimum (-11.91%) return values. On the other hand, the All-Share index had the lowest standard deviation of 1.06% and thus could be considered the least volatile index during this period.

The skewness values of all indices fell below one but above zero. This means that for the four indices, their returns data series were very close to being symmetric. However, when we compare the mean values to the median values for all indices, it can be noted that the mean > median condition is true in all cases. As such, we can confidently conclude that all returns data series for these indices had positively skewed data distributions in this period. The Kurtosis values for all indices fall way above three, and thus we can also note that all returns distributions have fat tails and can be described as leptokurtic. In the context of the returns data here, this indicates that the returns distribution of data across all indices shows a high level of risk. This is attractive for investors with a high-risk appetite and not favourable for risk averse investors.

Table 5. 2. Descriptive Statistics for two sub periods (Jan 2012-Dec 2016 and Jan 2017-Dec2021)

Descriptive Statistics and Sub Period	**JSE All Share**	**JSE Financial (15)**	**JSE Industrial (25)**	**JSE Resource (20)**
Mean (2012-2016)	-0.03%	-0.04%	-0.06%	0.05%
Mean (2017-2021)	-0.02%	0.02%	-0.02%	-0.05%
Median (2012-2016)	-0.06%	-0.10%	-0.12%	0.02%
Median (2017-2021)	-0.05%	-0.05%	-0.07%	-0.06%

Maximum (2012-2016)	3.69%	9.54%	3.97%	6.91%
Maximum (2017-2021)	10.8%	14.2%	9.55%	16.9%
Minimum (2012-2016)	-4.07%	-5.08%	-4.58%	-7.12%
Minimum (2017-2021)	-8.65%	-12.7%	-6.79%	-11.9%
S.D. (2012-2016)	0.93%	1.19%	0.97%	1.68%
S.D. (2017-2021)	1.18%	1.73%	1.23%	1.78%
Skewness (2012-2016)	0.33	0.71	0.22	0.14
Skewness (2017-2021)	0.96	0.76	0.56	0.82
Kurtosis (2012-2016)	1.33	4.97	1.50	1.56
Kurtosis (2017-2021)	14.2	12.2	5.28	12.6

Source: EViews output. Data from Thomson Reuters and IRESS (2022).

The purpose of this sub-period analysis is to compare and contrast any major changes of the descriptive statistics within and across the indices between the two sub periods. Glaringly clear at first glance is that the mean and median of all indices except the Resource (20) are higher in the 2017-2021 sub-period (sub-period 2) as compared to the 2012-2016 sub-period (sub-period 1). Adding on, the highest mean (0.05%) and median (0.02%) in sub period 1 came from the Resource (20) index as with the full period analysis. On the other hand, in sub-period 2, the highest mean (0.02%) comes from the Financial 15 index, while the highest median (-0.05%) is recorded for the Financial (15) and All Share indices. The standard deviation values are also higher in sub period 2 as compared to sub period 1, further reinforcing the positive relationship between risk and mean returns. The highest standard deviation (1.68%) in sub-period 1 and (1.78%) in sub period 2 come from the Resource (20) index making it the most volatile index. Note also that the All-Share index remains the least volatile index in both sub-periods with standard deviations of 0.93% and 1.18% in sub-period 1 and 2 respectively. With this in mind, it is logical to label sub-period 1 as a lower mean return, lower risk sub-period and sub-period 2 as a higher mean return, higher risk sub-period.

For skewness, both sub-periods across all indices recorded values close to zero. However, once again as seen with the full period analysis, the mean > median in both sub-period as such we conclude that the returns distribution of these indices is positively skewed. The Kurtosis values in sub-period 1 for the All Share (1.33), the Industrial (25) (1.5) and the Resource (20) (1.56) indices are less than 3. This means that the return distributions for these indices in sub period

1 are thin tailed and thus platykurtic. This entails small spikes in positive and negative returns thus less risk. It is therefore safe to note that period one would have been more aligned with risk averse investors. Sub-period 2 can be noted to indicate fat tailed and thus leptokurtic returns distribution (period of higher risk) since all kurtosis values are well above 3.

5.2.2 Trend Analysis.

In Financial Economics, trend analysis is a strategy commonly used to study past data patterns to try and predict future outcomes. However, for this research we simply intend to use this technique to understand how the variables of interest move over time across the four indices (JSE ALL-Share, Financial 15, Industrial 25 and the Resource 20). Note that all close price series across all indices show random walk with drift patterns and thus can be said to be non-stationary at level terms. On the other hand, the shock measures and the stock market turnover ratio (SMTURN) all seem to maintain a mean close to zero throughout time and thus visually are stationary in level terms.

5.2.2.1 Close Price trend analysis.

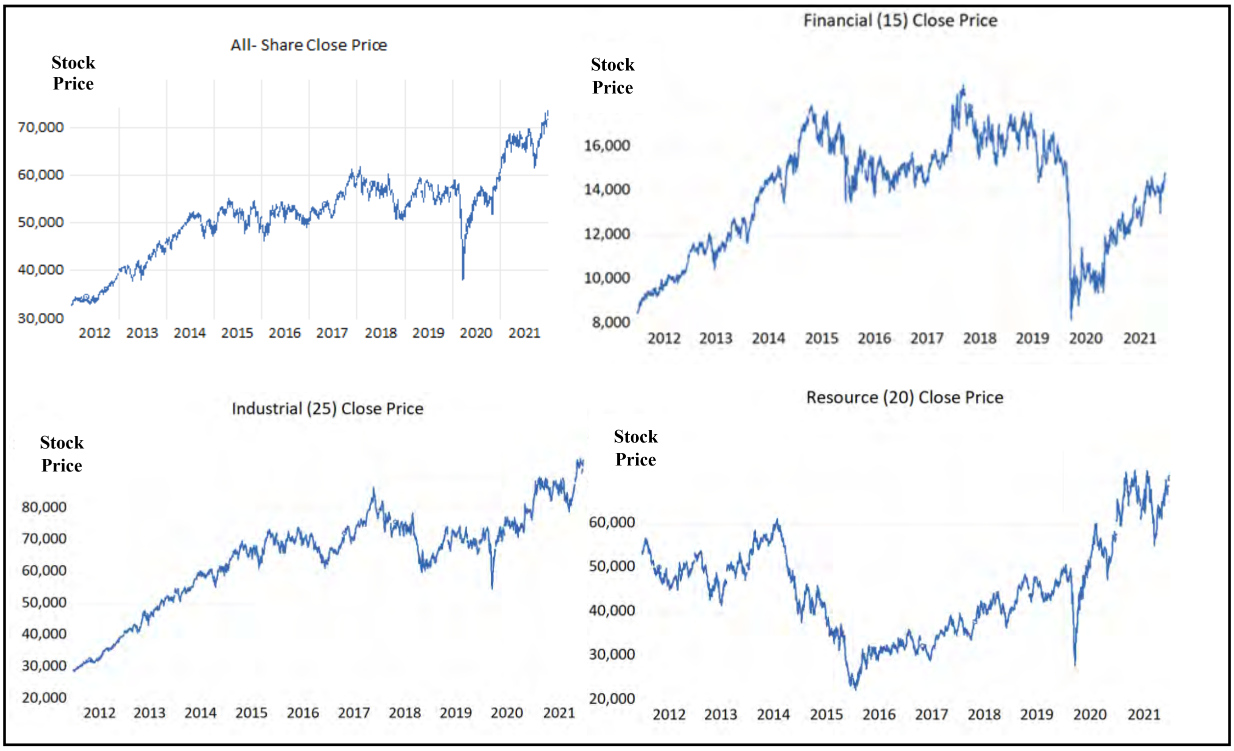

Figure 5. 1: Closing price (In Rands) trends for the All-Share index, Financial 15, Industrial 25 and Resource 20 (2012-2021).

Source: EViews: Using Thomson Reuters and IRESS (2022) data.

Here the aim is to pick out obvious trends and patterns in the variables above. The All-Share index close price shows a steady rise throughout the 2012-2021 period of analysis. A drastic dip in the All-Share close price is depicted around 2020. The Financial 15 index close price also rises up to 2015 before showing a non-deterministic trend up until 2020 when it also has a sharp decline. On the other hand, the Industrial 25 close price follows a similar upward trend as the All-Share closing price, the only difference being a smaller decline in 2020.Lastly, the Resource 20 index close price has a downward trend up to mid-2015 which turns upward for the rest of the period of analysis. Notice that all closing prices experience a sharp decline in between 2019 and 2020.

5.2.2.2 Amihud illiquidity Shocks trend analysis.

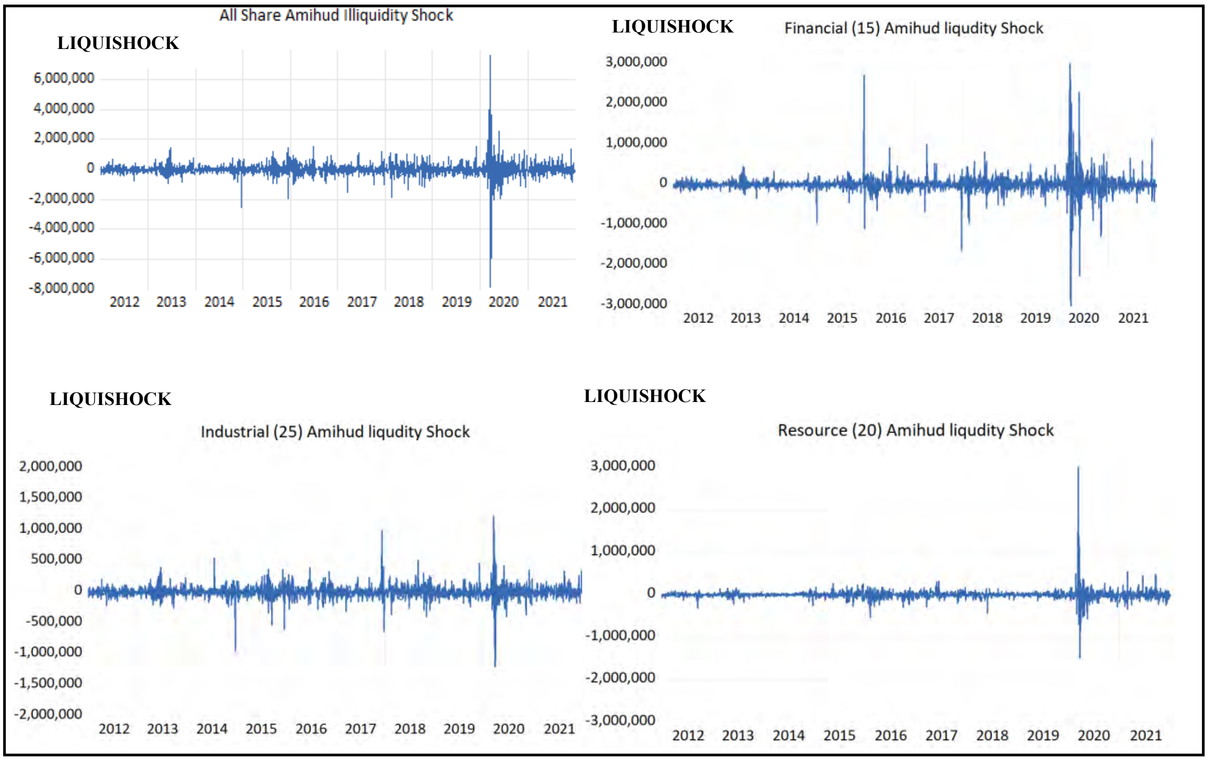

Figure 5. 2:Amihud illiquidity Shock trends for the All-Share, Financial 15, Industrial 25 and Resource 20 indices (2012-2021).

Source: EViews: Using Thomson Reuters and IRESS (2022) data.

The illustration above shows how the Amihud illiquidity shock behaves over time across the different indices. Notice that the most drastic illiquidity shocks are prominent in the Industrial 25 index followed by the All- Share index. Likewise, the least prominent illiquidity shocks here are seen in the Resource 20 index followed by the Financial 15 index. Adding on, it can also be seen that there is a consistent trend of clustered shocks between 2019 and 2020 across all the indices.

5.2.2.3 Change in Turnover Shocks trend analysis.

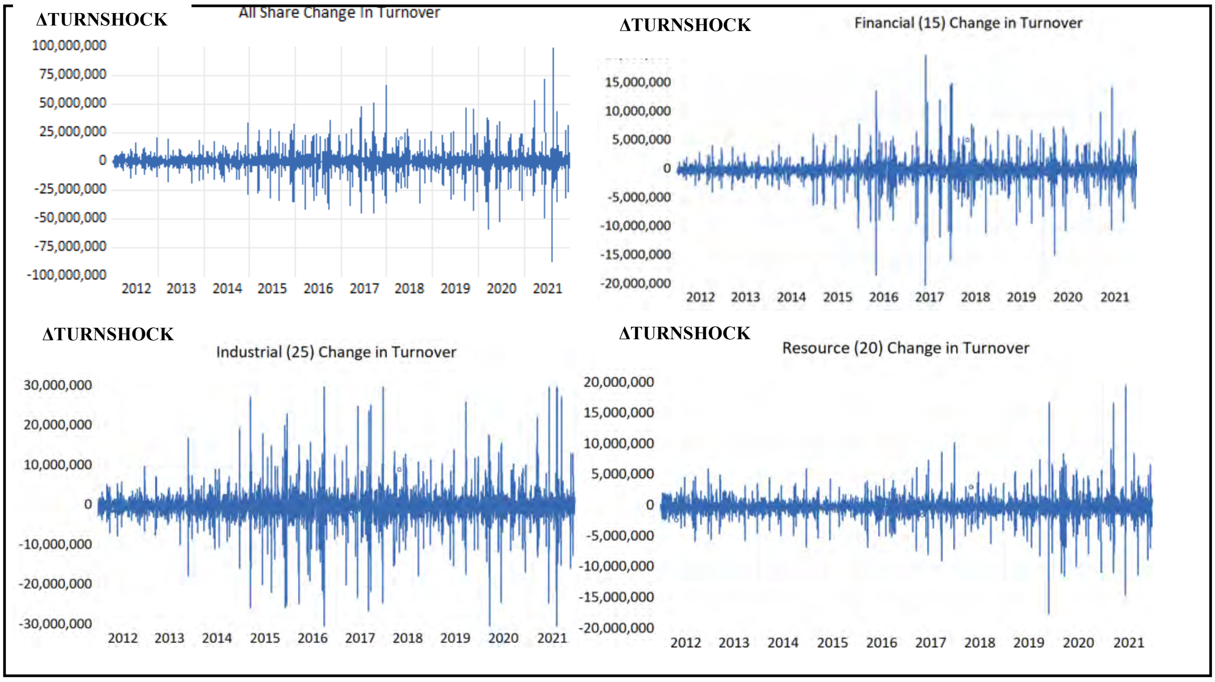

Figure 5. 3 : **Change in Turnover Shock trends for the All-Share, Financial 15, Industrial 25 and Resource 20 indices (2012-2021).**

Source: EViews: Using Thomson Reuters and IRESS (2022) data.

The illustration above shows how the Change in Turnover shock behaves over time across the different indices. Note here that as compared to the Amihud illiquidity shock above, the Change in Turnover Shock actually measures liquidity shocks which are the exact opposite of illiquidity shocks. Referring back to Figure 5.2, it can be seen that when the liquidity shocks are more prominent, the illiquidity shocks become dominant. As such, it can be seen above that the most prominent liquidity shocks are present in the All-Share index and the Resource 20 index. On the other hand, we note the Industrial 25 index to have the least prominent liquidity shocks. The Financial 15 index here shows moderate liquidity shocks over the period of analysis.

5.2.2.4 Stock Market Turnover Ratio trend analysis.

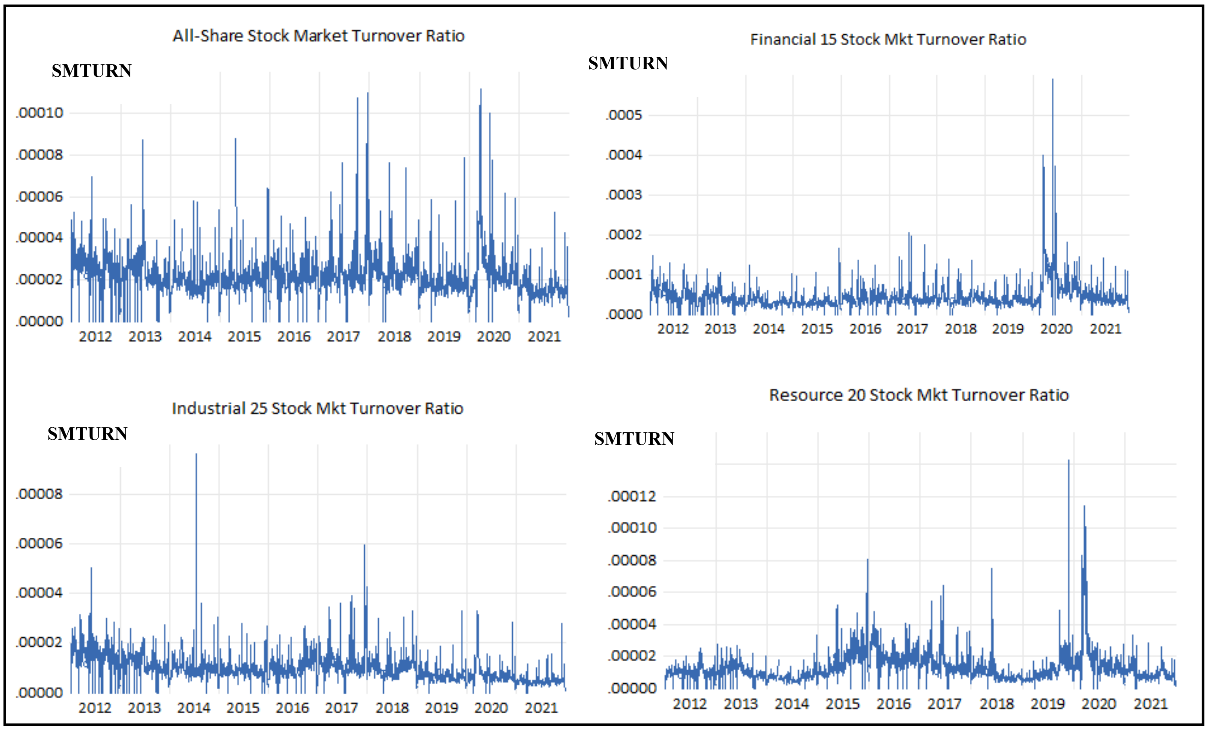

Figure 5. 4 : **Stock Market Turnover Ratio Trends for the All-Share, Financial 15, Industrial 25 and Resource 20 indices (2012-2021).**

Source: EViews: Using Thomson Reuters and IRESS (2022) data.

From above, we observe that the most volatile stock market turnover ratio is encountered in the All-Share index. The least volatile stock market turnover ratio here is seen in the Financial 15 index which is quite similar to the Resource 20 index. Note here that for both the Financial 15 and Resource 20 index, the stock market turnover ratio has drastic upward spikes between the 2019-2020 period.

5.3 Presentation and Analysis of Regression Results.

This section presents the results of the econometric and mathematical methods discussed in Chapter 4. These will be structured starting with the ARCH and GARCH results, followed by correlation analysis, unit root tests, cointegration tests, impulse response and variance decompositions and Granger Causality tests.

5.3.1 ARCH and GARCH Models.

As explained in Chapter 4, Section 4.3.4.2, this research makes use of the GARCH model residuals found on the tests of each return's series across the four indices under study to proxy volatility. For this to occur, the first test is to find out if ARCH effects and thus volatility clustering exists for each of the four returns time series. The tests conducted and therefore presented in Appendix A show that ARCH effects and thus volatility clustering were present in each of the four returns series. As can be noted in Appendix A, the probabilities of the F-Statistic and the Chi-Square where 0,0000, meaning that it was safe to reject the null hypothesis of homoscedasticity. The arch term (RESID (-1) ^2) also had a probability value of 0.0000 for all returns times series tested indicating significance at the 1% level and the ability of past volatility to predict future volatility on each index. Having established this basis, the research went on to estimate GARCH models. The results are shown in Table 5.3 below.

Table 5. 3. GARCH Test Results.

Index	ARCH Term	GARCH Term	Returns (-1)
All Share	0.096897*** (0.0000)	0.874902*** (0.0000)	-0.017474 (0.4236)
Financial (15)	0.105074*** (0.0000)	0.877141*** (0.0000)	-0.014249 (0.5179)
Resource (20)	0.059490*** (0.0000)	0.929109*** (0.0000)	0.016413 (0.4495)
Industrial (25)	0.082935*** (0.0000)	0.896734*** (0.0000)	-0.007205 (0.7308)

Notes: Statistically significant at the 1% (***).

Source: EViews output. Data from Thomson Reuters and IRESS (2022)

Table 5.3. above shows the ARCH term, GARCH term and the coefficient of the lag of returns and their probabilities in brackets for the four indices under study. The first thing to note is that both the ARCH and GARCH terms are significant at the 1% level across all four indices since their probability values are all 0.0000. Next, one can also deduce that the sum of the ARCH and GARCH term for each index is a number close to one better known as unity in this case. This means that there is volatility persistence in all the indices depicted above. Lastly, a look at the return's column shows that three of the four indices have a negative lagged coefficient of returns pointing at a negative relationship between past returns and current returns. However, since their probability values are all greater than 10%, this renders the coefficients insignificant, therefore it would be safe to highlight that past returns do not significantly influence current returns on any of the indices above. Using the Efficient Market Hypothesis discussed in Chapter 2, it can also be concluded that these indices are at the least weak form efficient. Most

important to this section, these results mean that the residuals extracted from these GARCH models will be good proxies of volatility for each of the return series of the indices above.

5.3.2 Correlation Analysis and Variance Inflation Factors (VIF).

One of the problems encountered when estimating an ARDL is multicollinearity. As such, this research makes use of correlation analysis to gauge the strength of correlation between independent variables which could lead to multicollinearity. Note here that correlation refers to the linear relationship between two variables (Brooks, 2014). It is important to indicate that correlation does not ascertain causality thus further tests on the variables in the following sections. The VIF tests shown in Appendix D will also show whether multicollinearity exists or not. Note that if the Cantered VIF statistic is greater than 10 for any of the variables, severe multicollinearity is present.

Table 5. 4. All Share independent variables correlation matrix

	LIQUISHOCK	**ΔTURNSHOCK**	**EXCH**	**VOLA**	**VOLU**
LIQUISHOCK	1.0000 -------				
ΔTURNSHOCK	-0.067490 0.0009	1.0000 --------			
EXCH	-0.002228 0.9125	0.017397 0.3907	1.0000 --------		
VOLA	-0.097041 0.0000	0.046395 0.0220	0.015276 0.4511	1.0000 --------	
VOLU	0.017518 0.3874	0.370849 0.0000	0.376859 0.0000	0.027076 0.1816	1.0000 ------

Source. EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

Table 5.4 above shows the All-Share variables used in the research and their correlation analysis. The matrix shows two numbers in each cell, the top one is the correlation coefficient and the bottom one is the probability value showing statistical significance for each of the five variables against the other. A correlation coefficient closest to +1 indicates a positive linear relationship while one closest to -1 indicates a negative linear relationship. Notice here that the correlation between change in turnover shocks and illiquidity shocks is disregarded because the two will be included in separate ARDL models. As such, the most statistically significant relationships in the matrix are between change in turnover shocks and trading volume, the exchange rate and trading volume, illiquidity shocks and conditional volatility, and lastly between change in turnover shocks and conditional volatility. These can be interpreted as follows; change in turnover shocks and trading volume have a relatively weak positive relationship (0.370849) significant at the 1%. This is quite similar to the correlation between the exchange rate and trading volume, which is also relatively weak, positive (0.376859) and significant at the 1% level. conditional volatility and illiquidity shocks share a weak negative relationship (-0.097041), significant at the 1%. Lastly, conditional volatility and change in turnover shocks share a weak positive relationship (0.046395), significant at the 5% level. From the matrix the positive relationship between conditional volatility and change in turnover shocks is expected since the change in turnover shocks variable is at its core derived from the trading volume of trades on the market.

Table 5. 5. Panel independent variables correlation matrix.

	LIQUISHOCK	ΔTURNSHOCK	EXCH	VOLA	VOLU
LIQUISHOCK	1.0000				

ΔTURNSHOCK	-0.027125	1.0000			
	0.0209	--------			
EXCH	0.007131	0.012781	1.0000		
	0.5437	0.2764	--------		
VOLA	-0.036314	0.028053	0.019022	1.0000	
	0.0020	0.0169	0.1053	--------	
VOLU	0.067334	0.275689	0.222222	0.022575	1.0000
	0.0000	0.0000	0.0000	0.0545	--------

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022).

Table 5.5.is a replica of Table 5.4 but with a focus on the panel data variables. The panel is made up of the Financial 15, Industrial 25 and Resource 20 indices. The variables are the same as with Table 5.4 only that they are running across the three indices as opposed to just the one in Table 5.4. At first glance, it is noticeable that trading volume is significantly and positively related to illiquidity shocks, change in turnover shocks, the exchange rate and conditional volatility at the 1%, 1%, 1% and 10% level respectively. The strongest of these relationships with trading volume, although still weak, is shared with change in turnover shocks and the exchange rate with correlation coefficients of 0.275689 and 0.222222 respectively. Adding on, VOLA and illiquidity shocks share a weak negative relationship (-0.036314), significant at the

1%. Lastly, VOLA and change in turnover shocks share a weak positive relationship (0.028053), significant at the 5% level.

Notice that none of the above correlations are strong enough to result in multicollinearity of the independent variables. However, it is worth noting that trading volume is correlated significantly to more than one variable in both Table 5.4 and 5.5, meaning that the resultant effect could lean towards multicollinearity. Furthermore, to concrete the non-existence of multicollinearity, VIF tests were also conducted on the time series independent variables. It is then noted that all variables had a cantered VIF statistic less than 10 indicating that there is no severe case of multicollinearity. These results are shown in Appendix D.

5.3.3 Unit Root Tests and Panel Cointegration Tests.

5.3.3.1 Unit Root Tests.

The unit root tests conducted in this section pave way for the cointegration tests in the next section. As discussed in Chapter 4, an ARDL precaution taken is that no variable be integrated of order 2. As such the research variables namely the stock market turnover ratio (SMTURN), the Amihud illiquidity shock (LIQUISHOCK), the change in turnover shock (ΔTURNSHOCK), the spot exchange rate (EXCH), conditional volatility (VOLA) and trading volume (VOLU) are taken through unit root tests to determine if they become stationary at level terms I (0) of at first difference terms I (1). If it is found that all variables, are I (1), then the research can proceed to conduct cointegration tests. Note again that the research carries out a time series ARDL on the JSE All Share index and a panel ARDL which includes the Financial (15) Resource (20) and Industrial (25) indices as mentioned in Chapter 4. We therefore carry out individual unit root tests for variables in the time series ARDL shown in Section 5.3.3.1.1. and panel unit root tests for those in the panel ARDL shown in Section 5.3.3.1.2.

Note that before conducting any unit root tests, each variable was run against its own constant and trend to determine their significance and thus whether to include them in the stationarity tests. As is depicted in the tables below in the model column, only the change in turnover shocks variable had both constant and trend insignificant. Otherwise, it was found that stock market turnover ratio, trading volume and the exchange rate had significant constants and trend, while illiquidity shocks and conditional volatility only had a significant constant.

5.3.3.1.1 Augmented Dicky Fuller and the Phillips Perron Tests.

Table 5. 6. All Share Time Series Unit Root Test Results at level terms I (0).

Variable	**Model**	**ADF**	**PP**
SMTURN	Intercept and Trend	-12.6917*** (0.0000)	-44.13995*** (0.0000)
LIQUISHOCK	Intercept	-18.9501*** (0.0000)	-57.47889 (0.0001)
ΔTURNSHOCK	None	-25.5911*** (0.0000)	-432.288*** (0.0001)
EXCH	Intercept and Trend	-2.61318 (0.2744)	-2.62535 (0.2689)
VOLA	Intercept	-18.0902*** (0.0000)	-51.8545*** (0.0001)
VOLU	Intercept and Trend	-14.5893*** (0.0000)	-41.8977*** (0.0000)

Notes: Statistically significant at the: 1% (***)

Source: EViews output, data from Thomson Reuters (2022) and IRESS (2022).

Table 5. 7 All Share Time Series Unit Root Test integrated of order 1 (1).

Variable	**Model**	**ADF**	**PP**
D (EXCH)	Intercept and Trend	-49.8108*** (0.0000)	-49.8103*** (0.0000)

Notes: Statistically significant at 1% (***).

Source: EViews output, data from Thomson Reuters (2022) and IRESS (2022).

Table 5.6 and 5.7 above show the results of the Augmented Dicky Fuller (ADF) and the Phillips Perron unit root tests. The null hypothesis for both tests is that a series has a unit root (non-stationary). Therefore, if a test statistic from either test is insignificant or larger than 10%, the series has a unit root and thus can be considered nonstationary. Hence or otherwise the time series does not have a unit root and can be considered stationary. At level terms (integrated of order zero), in Table 5.4., the variables stock market turnover ratio, change in turnover shocks, trading volume and conditional volatility all had significant test statistics for both the ADF and PP at the 1% level of significance. As such, the null hypothesis is rejected leading to the conclusion that the latter variables are stationary in level terms or I (0). the exchange rate is however found to have. insignificant test statistics for both the ADF and PP at the 10% level of significance. Therefore, the exchange rate is nonstationary at level terms. As such, another test in first difference terms is conducted on the exchange rate and the results displayed in Table 5.5. Here, both the ADF and PP test statistics were both significant at the 1% level as such, the null hypothesis of a unit root is rejected. It is therefore deduced that the exchange rate is stationary in first difference terms or I (1).

5.3.3.1.2 Panel Unit Root Tests.

Table 5. 8 Panel Unit root tests at level terms I (0).

Variable	**Model**	**LLC**	**IPS**	**ADF-Chi Square**
SMTURN	Intercept and Trend	-17.6841*** (0.0000)	-15.8802*** (0.0000)	248.468*** (0.0000)
LIQUISHOCK	Intercept	-19.1332*** (0.0000)	-31.5713*** (0.0000)	555.995*** (0.0000)
ΔTURNSHOCK	No intercept or Trend	-38.1000*** (0.0000)	N/A	534.868*** (0.0000)
EXCH	Intercept and Trend	-0.18325 (0.4273)	-0.9777 (0.1641)	7.75986 (0.2562)
VOLA	Intercept	-117.936*** (0.0000)	-99.3634*** (0.0000)	55.2620*** (0.0000)
VOLU	Intercept and Trend	-24.8992*** (0.0000)	-23.7693*** (0.0000)	448.838 (0.0000)

Notes: Statistically significant at 1% (***)

Source: EViews output, data from Thomson Reuters (2022) and IRESS (2022).

Table 5. 9 Panel Unit Root Tests integrated of order 1 I (1).

Variable	**Model**	**LLC**	**IPS**	**ADF Chi-Square**
D (EXCH)	Intercept and Trend	-168.812*** (0.0000)	-106.780*** (0.0000)	790.172*** (0.0000)

Notes: Statistically significant at 1% (***)

Source: EViews output, data from Thomson Reuters (2022) and IRESS (2022).

Table 5.8 and 5.9 above show the panel unit root tests conducted using the Livin, Lin and Chu (LLC), Im, Pesaran and Shin (IPS) and the Augmented Dicky- Fuller Chi-Square tests. Here the null hypothesis for all tests states that a series has a unit root (non-stationary). All three test statistics were found to be significant at the 1% level for stock market turnover ratio, illiquidity shocks, conditional volatility and trading volume. Therefore, the null hypothesis is rejected for all the latter variables meaning that they are all stationary at level terms and can be classified as I (0). Adding on, since change in turnover shocks have no significant trend or intercept, the IPS test is null. However, both the LLC and ADF Chi-Square test statistics are significant at the 1% and thus indicate stationarity at level terms for change in turnover shocks. The results in Table 5.6 also show that the exchange rate has insignificant test statistics across the three tests indicating a unit root and thus non-stationarity for the variable at the 10% level. Table 5.7 therefore shows the results of the first difference unit root tests on the exchange rate. Here, the test statistics of the LLC, IPS and ADF Chi-Square are all found to be significant at the 1% level as such we are able to sufficiently reject the null. This means that the exchange rate becomes stationary in first difference terms and can be classified as I (1).

At this juncture, the research has managed to conduct pre-check tests to ensure that the ARDL model is most appropriate. As highlighted by Humpe and McMillan (2020), the variables of this research are of mixed order of integration (I (0) and I (1)) and therefore are adequate to have cointegration tests run under the ARDL. Furthermore, correlation and VIF tests indicated that the independent variables in the two models to be estimated are not suffering from multicollinearity which helps to keep the ARDL results true.

5.3.4 Cointegration Test Results.

Remember that this section aims to answer the overarching goal and its two sub-goals outlined in Chapter 1 Section 1.3. The first subgoal looks at the relationship between stock market efficiency (SMTURN) and stock market liquidity shocks (LIQUISHOCK and ΔTURNSHOCK). As capital markets which are represented by the All-Share index in this research. The results for this sub goal are found using the time series ARDL below. In the second subgoal, the later relationship is evaluated across three indices (Financial 15, Industrial 25 and Resource 20) which make up the panel in this section. Results in the panel ARDL model and cross-sectional short run results address this sub goal.

Table 5. 10. Time Series ARDL estimators of the All-Share Index with Change in Turnover shock (ΔTURNSHOCK).

Variables	Coefficients	Standard Error	Probability
Long Run Equation			
ΔTURNSHOCK	7.85 E-13	3.34E-13	0.0190
EXCH	-1.76E13	2.34E-07	0.0000
VOLA	0.000862	0.000161	0.0000
VOLU	8.60E-14	6.64E-15	0.0000
C	2.41E-05	2.71E-06	0.0000
Short Run Equation			
ECT	-0.073004	0.006511	0.0000
D(ΔTURNSHOCK)	-8.36E-15	4.03E-15	0.0380
D(EXCH)	2.76E-07	2.58E-07	0.2848
D(VOLA)	2.34E-07	3.08E-06	0.9394
D(VOLU)	8.61E-14	4.65E-16	0.0000

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

The table above illustrates the results of a time series ARDL with stock market turnover ratio (SMTURN) as the dependent variable. An ARDL (4,4,1,4,4,) is automatically chosen in EViews using the Akaike Information Criterion. The model computes 2254 observations. The independent variable of concern is change in turnover shocks supported by control variables the exchange rate, conditional volatility and trading volume. Before delving into the results displayed consider the Bounds test results in the Appendix B. The bounds test indicates whether there exists a long-run relationship between the dependent variable and the independent variables thus cointegration. Here it is noted that the Bounds test F-Statistic is greater than both the lower and upper bound values at all levels of significance therefore the null hypothesis of no relationships is rejected. As such, the conclusion is that there exists a long-run relationship (cointegration) between the dependent variable stock market turnover ratio, and the independent variables shown in the table. With that in mind, each independent variable can now be interpreted in relation to stock market turnover ratio. Change in turnover shocks have a positive long run relationship which is significant at the 5% level. However, it is also noted that the coefficient of change in turnover shocks is quite small, thus it can be said to cause small positive changes in SMTURN in the long run. conditional volatility and trading volume both significantly (at the 1%) influence stock market turnover ratio positively in the long run. the exchange rate is the only variable influencing stock market turnover ratio negatively and significantly at the 1 % level.

For the short run, the first point of call is the Error Correction Term (ECT). Notice that the ECT term (-0.073004) is significant at the 1% and negative. This means that about 7.3% of the discrepancies faced in the short run for stock market turnover ratio will be restored to equilibrium each period. Furthermore, notice that unlike in the long run, change in turnover shocks influence stock market turnover ratio negatively and significantly at the 5% in the short run. trading volume maintains a positive relationship significant at the 1% while the exchange rate and conditional volatility indicate a positive but insignificant short run relationship with stock market turnover ratio. Now relating these findings to what was covered in Chapter 2 and 3 on the theory and existing empirical studies. Empirical studies and theory from Chordia, Roll and Subrahmanyam (2008) highlighted that periods of higher volatility result in higher stock market efficiency. In both the short-run and long run, it has been found that trading volume a proxy for stock market liquidity positively influences stock market turnover ratio (proxy for SME), thus agreeing with the existing findings. Another critical finding here is that the change in turnover shocks influence stock market turnover ratio both in the short run and long run although in opposing directions.

Table 5. 11. Time Series ARDL estimators of the All-Share Index with the Amihud illiquidity Shock (LIQUISHOCK).

Variables	**Coefficients**	**Standard Error**	**Probability**
Long Run Equation			
LIQUISHOCK	1.86E-11	4.42E-12	0.0000
EXCH	-1.67E-06	2.52E-07	0.0000
VOLA	0.000271	0.000115	0.0187
VOLU	8.32E-14	7.05E-15	0.0000
C	2.34E-05	2.91E-06	0.0000
Short Run Equation			
ECT	-0.067861	0.005814	0.0000
D(LIQUISHOCK)	3.07E-14	8.64E-14	0.7223

D(EXCH)	2.60E-07	2.57E-07	0.3116
D(VOLA)	-3.26E-06	3.05E-06	0.2850
D(VOLU)	8.47E-14	3.57E-16	0.0000

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

The above table is very similar to Table 5.10 in every way except the inclusion of a different shock measure, LIQUISHOCK (illiquidity shocks). An ARDL (4,4,1,1,4) is automatically chosen using the Akaike Information Criterion in EViews. The model goes through 2254 observations. Since the aim here is to test the relationship between illiquidity shocks and the dependent variable stock market turnover ratio. Once again, beginning with the Bounds test, from the results shown in Appendix B, it is clear that the null hypothesis of no long-term relationship is rejected for all levels of significance. Therefore, the conclusion is that illiquidity shocks and the other control variables in the table share a long-term relationship with stock market turnover ratio. Individually, illiquidity shocks share a positive long-term relationship with stock market turnover ratio that is significant at the 1%. conditional volatility and trading volume both positively influenced stock market turnover ratio in the long run significantly at the 5% and 1% respectively. Once again as noted in Table 5.10, the exchange rate is shown to influence stock market turnover ratio negatively in the long run at the 1% level.

In the short run results, the ECT (-0.067861) is found to be significant and negative at the 1% level. This means that when illiquidity shocks are involved, about 6.8% of the discrepancies in stock market turnover ratio are restored to equilibrium in each period. Notice that in comparison to Table 5.10 where change in turnover shocks are the shock applied, the speed of adjustment is a bit quicker (7.3%). Furthermore, the results also show that both illiquidity shocks and the exchange rate share a positive but insignificant relationship with the dependent variable. conditional volatility was found to have a negative and insignificant short run relationship while trading volume stays consistent with a positive and significant short run relationship with stock market turnover ratio. As with the previous results note again that the relationship between trading volume and stock market turnover ratio is per our priori expectations from literature and empirical studies. More important to this research is that illiquidity shocks only influence stock market turnover ratio positively and significantly in the long run. This could mean that short run liquidity shocks as measured by the Amihud method do not affect stock market efficiency at all.

Table 5. 12. Pooled Mean Group Panel ARDL with the change in turnover shock (ΔTURNSHOCK) and the Amihud Illiquidity shock (LIQUISHOCK).

	ΔTURNSHOCK Model		
Variables	**Coefficients**	**Standard Error**	**Probability**
Long Run Equation			
ΔTURNSHOCK	-2.13E-10	2.68E-11	0.0000
EXCH	1.57E-06	6.61E-07	0.0175
VOLA	0.002924	0.000424	0.0000
Short Run Equation			
ECT	-0.060642	0.034350	0.0775
D(ΔTURNSHOCK)	1.29E-11	7.30E-12	0.0770
D(EXCH)	3.99E-07	4.13E-07	0.3348
D(VOLA)	-0.000159	7.40E-05	0.0315
	LIQUISHOCK Model		
Variables	**Coefficients**	**Standard Error**	**Probability**
Long Run Equation			
LIQUISHOCK	6.68E-11	9.87E-12	0.0000
EXCH	-6.08E-07	1.20E-07	0.0000
VOLA	-0.000219	8.71E-05	0.0119
Short Run Equation			
ECT	-0.236343	0.045115	0.0000
LIQUISHOCK	-4.42E-12	4.25E-12	0.2984
D(EXCH)	2.27E-06	8.32E-07	0.0064
D(VOLA)	5.28E-05	1.05E-05	0.0000

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

The results shown in the table above represent the Pooled Mean Group (PMG) ARDL model testing the dependent variable stock market turnover ratio against stock market liquidity shocks (LIQUISHOCK and ΔTURNSHOCK) across three industries. As such we run two models, one for each shock. This section aims to answer the second sub-goal of the research. Note here that for the PMG ARDL analysis in EViews, the variable trading volume had to be excluded due to its significant correlation with change in turnover shocks and the exchange rate. For the change in turnover shocks model, the results show that at the 1 % level of significance, a negative long-run relationship exists with the dependent variable. the exchange rate and conditional volatility both share a positive and significant long run relationship at the 5% and 1% level. In the short run equation, the ECT (-0.060642) is negative and significant only at the 10%. This entails a relatively weak speed of adjustment to equilibrium. In other words, one would expect about 6% of the discrepancies in the short run to be corrected back to equilibrium each period. Individually, the change in turnover shocks influenced stock market turnover ratio positively and significantly (at the 10%) in the short run. the exchange rate had a positive but insignificant relationship while conditional volatility had a negative and significant relationship with stock market turnover ratio in the short run.

Now, turning our attention to the illiquidity shocks model, note that in the long run, illiquidity shocks had a positive relationship with stock market turnover ratio, significant at the 1%. the exchange rate and conditional volatility both had negative long run relationships with the dependent variable significant at the 1% and 5% level respectively. In the short run, the ECT (-0.236343) is negative and significant at 1% level. This is a much faster speed of adjustment when compared to the change in turnover shocks model. It entails that about 23.6% of the discrepancies would be corrected back to equilibrium in each period. The effect of illiquidity shocks in the short run is found to be negative and insignificant. The exchange rate and conditional volatility were both found to influence stock market turnover ratio positively and significantly at the 1% in the short run.

These results pave the way to answer the research objective of whether the liquidity shocks found here to influence stock market turnover ratio in the long run have a homogenous effect across the three sectors of the JSE mentioned earlier. This is done using the Cross-Sectional short run PMG Model as shown below.

Table 5. 13. Cross-Sectional Short-Run results from the PMG Model.

ΔTURNSHOCK				LIQUISHOCK			
Variable	**Coefficients**	**Std Error**	**Prob**	**Variable**	**Coefficients**	**Std Error**	**Prob**
	Financial (15)				**Financial (15)**		
ECT	-0.125595	0.000197	0.0000	**ECT**	-0.233605	0.000351	0.0000
D(ΔTURNSHOCK)	2.67-E11	2.34E-24	0.0000	**D(LIQUISHOCK)**	-2.23E-12	6.96E-24	0.0000
D(EXCH)	1.22E-06	5.57E-12	0.0000	**D(EXCH)**	3.92E-06	1.20E-11	0.0000
D(VOLA)	-0.000295	1.64E-09	0.0000	**D(VOLA)**	5.60E-05	1.02E-11	0.0000
	Industrial (25)				**Industrial (25)**		
ECT	-0.008787	1.59E-06	0.0000	**ECT**	-0.315816	0.000566	0.0000
D(ΔTURNSHOCK)	1.92E-12	1.58E-26	0.0000	**D(LIQUISHOCK)**	-1.26E-11	7.71E-24	0.0000
D(EXCH)	2.45E-08	3.22E-13	0.0000	**D(EXCH)**	1.62E-06	4.93E-13	0.0000
D(VOLA)	-4.07E-05	4.80E-11	0.0000	**D(VOLA)**	6.92E-05	6.97E-10	0.000
	Resource (20)				**Resource (20)**		
ECT	-0.047543	3.90E-05	0.0000	**ECT**	-0.159607	0.000248	0.0000
D(ΔTURNSHOCK)	1.01E-11	2.95-E25	0.0000	**D(LIQUISHOCK)**	1.60E-06	5.67E-24	0.0000
D(EXCH)	-5.26E-08	5.25E-13	0.0000	**D(EXCH)**	1.26E-06	1.04E-12	0.0000
D(VOLA)	-0.000142	2.16E-10	0.0000	**D(VOLA)**	3.32E-05	2.16E-10	0.0000

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

The table above illustrates the short-run cross sectional results for the ΔTURNSHOCK and LIQUISHOCK model. The dependent variable is still stock market turnover ratio. Note that the probability values for all the short-run variables is less than 1% hence they are all significant at that level. Starting off with the ECT terms, for both models across the three indices. It can be seen that they are all significant and negative meaning that the discrepancies in each index, whether during a change in turnover shock or Amihud illiquidity shock in the short run will dissipate in the long run. Generally, it is also clear that the speed of adjustment under the LIQUISHOCK model is better that that ΔTURNSHOCK across all three indices. The fastest speed of adjustment to equilibrium in the LIQUISHOCK model comes from the Industrial (25) index at 31.6% in each period while the slowest is given by the Resource (20) index at about 16% in each period. On the other hand, the Financial (15) index gave the fastest speed of adjustment to equilibrium (12.6% per period) while the Resource (20) index gave the slowest speed of adjustment (4.8%) under the ΔTURNSHOCK model. Notice that the Resource (20) index has the slowest speed of adjustment in both models. This could be as a result of it being the most volatile index as indicated by the descriptive statistics earlier.

Adding on, under the ΔTURNSHOCK model, the short run relationship between the change in turnover shock and stock market turnover ratio is consistently positive and significant across all three indices. However, under the LIQUISHOCK model, stock market turnover ratio only shared a positive relationship with the Resource (20) index while the Financial (15) and Industrial (25) indices shared a negative short run relationship with the dependent variable. Holistically, it can be highlighted that the change in turnover shocks and illiquidity shocks influence stock market turnover ratio in opposite directions holding all else constant. More conclusively, one is now able to answer the second sub goal of the research by saying that the change in turnover shock had a positive homogenous effect across all three indices' SME while the Amihud illiquidity shock had a negative homogenous effect on two of the three indices' SME in the short run.

5.3.5 Variance Decomposition and Impulse Responses.

This section deals with the impulse response functions (IRF) and variance decompositions (VD) designed to aid in understanding more about the relationships between our variables when shocks are applied to the system. Since the main concern is the relationship between the stock market efficiency variable stock market turnover ratio and liquidity shocks (LIQUISHOCK and ΔTURNSHOCK), we ignore variables' responses to shocks on themselves (for example response of SMTURN-to-SMTURN shocks). Note that the VD and IRF results below are derived using a Vector Error Correction Model VECM model as opposed to a simple VAR because both shock measure variables are I (1) and share long run relationships with stock market turnover ratio as was discussed earlier. The aim now is to understand and visually see the distribution of shocks of one variable on the other.

5.3.5.1 All Share Impulse Response Functions for ΔTURNSHOCK and LIQUISHOCK with SMTURN.

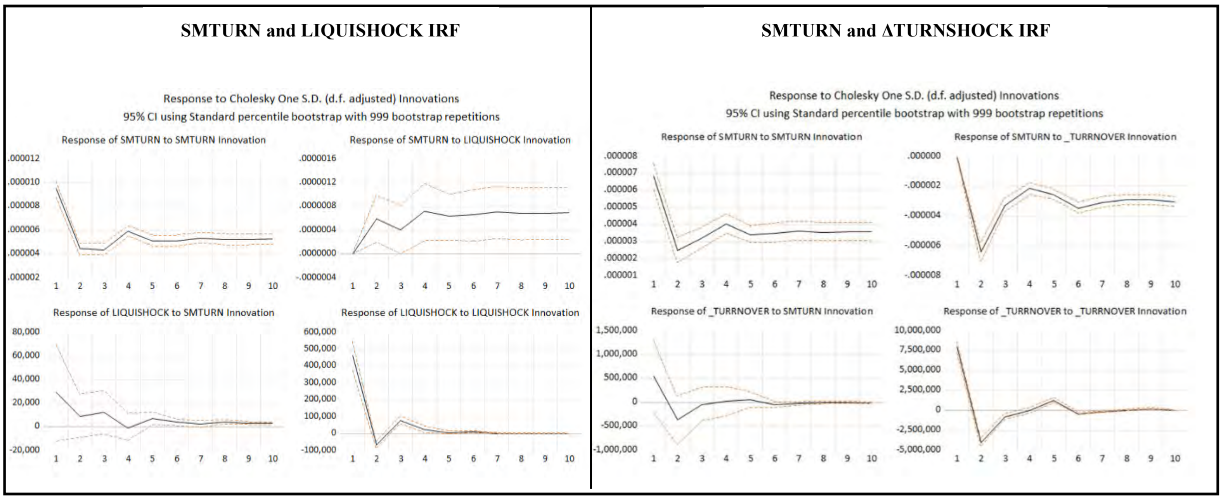

Figure 5. 5. All Share LIQUISHOCK, ΔTURNSHOCK and SMTURN impulse response functions.

Source: EViews: Using Thompson Reuters (2022) and IRESS (2022) data.

Figure 5.5 depicts IRFs between stock market turnover ratio and illiquidity shocks, and stock market turnover ratio and change in turnover shocks. In the stock market turnover ratio and illiquidity shocks illustration, within a 95% confidence interval, a one standard deviation shock (innovation) in illiquidity shocks results in a positive response shown by the upward movement in stock market turnover ratio for the first two periods. A downward trend ensues between the second and third period before the shock wears off in period five onwards after a slight upward response. On the other hand, a one standard deviation shock on stock market turnover ratio initiates a downward response for illiquidity shocks from period one to four. The shock then wears off around period five as illiquidity shocks become stable again. Comparing these findings to the variance decomposition (VD) results in Appendix C, firstly note that periods one to five depict the short run while periods 6 to ten represent the long run. It was found that the maximum error variance in stock market turnover ratio explained by illiquidity shocks is about 1% attained only in the long run. In the same light, the influence of stock market turnover ratio on illiquidity shocks remained well under 1% in both the short and long run. These results reinforce the time series ARDL results found in Table 5.11 that illiquidity shocks only share a significant relationship with stock market turnover ratio only in the long run and not the short run.

In the stock market turnover ratio and change in turnover shocks illustration, a one standard deviation shock to change in turnover shocks has a noticeable negative impact on stock market turnover ratio in the first two periods. This causes stock market turnover ratio to fall below zero. From period two onwards, the response of stock market turnover ratio becomes positive up to period 4 where the shock wears off and stock market turnover ratio reaches a steady state that is still however negative due to the initial change in turnover shock. Adding on, notice a similarity between the response of ΔTURNSHOCK to SMTURN and LIQUISHOCK to SMTURN above. Here it is also seen that a one standard deviation shock to stock market turnover ratio results in a negative response in the change in turnover shock until the shock wears off and it becomes stable again in period 5 onwards. Turning to the VD, it was found that period 3 (the short run) showed the highest error variance on stock market turnover ratio caused by the change in turnover shocks of about 45%. This slightly drops in the long run to 41%. Remember that in Table 5.10, the change in turnover shocks had a significant relationship with stock market turnover ratio in both the short and long run thus. Here this result is echoed. stock market turnover ratio showed an error variance less than 1% on change in turnover shocks in all periods.

5.3.5.2 Panel Impulse Response Functions for ΔTURNSHOCK and LIQUISHOCK with SMTURN.

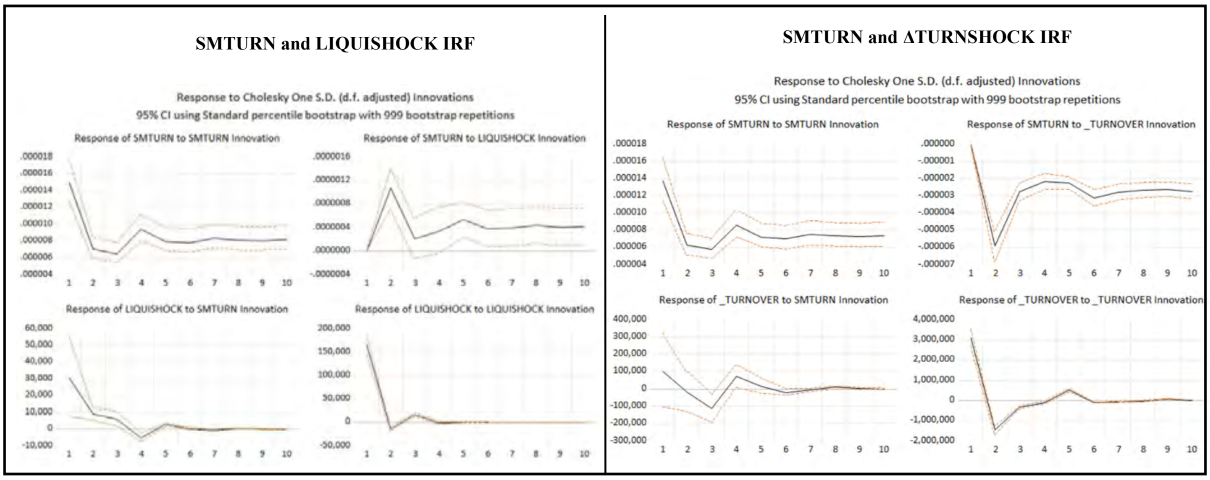

Figure 5. 6. Panel LIQUISHOCK, ΔTURNSHOCK and SMTURN impulse response functions.

Notice that Figure 5.6 illustrations are very similar to Figure 5.5. This gives us the impression that bidirectional shocks between stock market efficiency (SMTURN) and stock market liquidity shocks (LIQUISHOCK and ΔTURNSHOCK) are similar whether through the All - Share lens or the Panel (Financial, Industrial, Resource) lens. Figure 5.6 is therefore interpreted as follows; from the stock market turnover ratio and illiquidity shocks illustration, a one standard deviation shock in illiquidity shocks caused a noticeable sharp upward response followed by a downward response in stock market turnover ratio within the first three periods. Afterwards, the shock wears off although still causing a slight upward response in stock market turnover ratio before in becomes stable in period 6 onwards above zero. Adding on, a one standard deviation shock is also seen here to cause a downwards response to illiquidity shocks up until it wears off and illiquidity shocks becomes stable at zero. In terms of the Variance Decomposition results shown in Appendix C, the error variance in stock market turnover ratio explained by illiquidity shocks is weak and falls from 0.42% in period 2 to 0.30% in the long run (period 10). The stock market turnover ratio was seen to constantly influence about 3% of the variance in illiquidity shocks in both the short run and long run. These results can be noted to somewhat agree with the panel ARDL results in Table 5.12 where the long and short run relationships between illiquidity shocks and stock market turnover ratio are significant but with very small coefficients.

Turning to the stock market turnover ratio and change in turnover shocks illustration, it can be seen that stock market turnover ratio responds with a sharp negative drop to a one standard deviation shock in change in turnover shocks up until period 2. Thereafter, the response in stock market turnover ratio becomes positive until the shock wears off in period 4 and stock market turnover ratio regains stability although below zero. As with the other stock market turnover ratio shocks, a one standard deviation shock in stock market turnover ratio here caused a downward change in turnover shocks response until period 3. A slight positive response is seen between period 4 and 5 until the shock weakens and change in turnover shocks become stable from period 6 onwards. Turning to the VD results, it was seen that the error variance in stock market turnover ratio explained by change in turnover shocks reaches a peak of 14% in the short run then drops to 12% in the long run. This coincides with the panel ARDL results in Table 5.12 where change in turnover shocks share a significant relationship with stock market turnover ratio over time. On the other hand, stock market turnover ratio's influence on change in turnover shocks is very weak shown by error variances less than 0.5% in both the short and long run.

Our findings in both Figures 5.5 and 5.6 gave a clearer picture of how immediate the shocks of each variable affect the other and how long the effects last. As highlighted above, most shocks weaken and disappear by the fifth period. The shocks of both illiquidity shocks and change in turnover shocks on stock market turnover ratio are not fixed over time. We note that, the response of stock market turnover ratio is not consistently positive or negative after the shocks from either variable. However, illiquidity shocks are seen to leave stock market turnover ratio in a positive steady state while change in turnover shocks leave stock market turnover ratio in a negative steady state. Overall, it was also seen that stock market turnover ratio shocks both for the Panel and All Share variables consistently resulted in a negative response for both illiquidity shocks and change in turnover shocks up until they reached steady state at zero. It can be inferred from this that stock market efficiency shocks reduce the occurrence of liquidity shocks.

5.3.6 Granger causality tests.

This section provides a further analysis on the relationship between stock market efficiency and stock market liquidity shocks. Granger causality tests defined in Chapter 4 can also be used as a post estimation analysis for the ARDL models estimated earlier. Having established the existence of short-run and long run relationships, considered the IRFs, Granger Causality tests will also concrete our findings in this regard. The null hypothesis outlined are rejected if the corresponding probability values are less than 10%, 5% and 1%.

Table 5. 14. Granger Causality Results for All Share and Panel variables of interest.

Null Hypothesis	**F-Statistic**	**Probability**
All Share Variables Causality Results		
LIQUISHOCK does not Granger Cause SMTURN	4.52317	0.0109
SMTURN does not Granger Cause LIQUISHOCK	1.55753	0.2109
ΔTURNSHOCK does not Granger Cause SMTURN	1012.03	0.0000
SMTURN does not Granger Cause ΔTURNSHOCK	58.0346	2E-25
Panel Variables Causality Results		
LIQUISHOCK does not Granger Cause SMTURN	20.0296	3E-30
SMTURN does not Granger Cause LIQUISHOCK	9.82437	1E-13
ΔTURNSHOCK does not Granger Cause SMTURN	183.351	7E-28
SMTURN does not Granger Cause ΔTURNSHOCK	2.81159	0.0041

Source: EViews. Data from Thomson Reuters (2022) and IRESS (2022).

Starting off with the All-Share variables in the table above, it was found that a unidirectional relationship exists between illiquidity shocks and stock market turnover ratio. At the 5% level of significance of significance, the null hypothesis that illiquidity shocks do not Granger Cause stock market turnover ratio is rejected. In the same light, we failed to reject the null that stock market turnover ratio does not Granger Cause illiquidity shocks even at the 10% level. These results agree with the VD interpretations earlier where stock market turnover ratio was noted to weakly influence less than 1% variance in illiquidity shocks over time. Adding on, it was also found that a bidirectional relationship exists between stock market turnover ratio and change in turnover shocks for the All-Share data variables since both null hypotheses were rejected at the 1% level.

In the panel data variable section, the probability values for the illiquidity shocks and stock market turnover ratio relationship are both less than 1%. As such, it can be concluded that illiquidity shocks Granger cause stock market turnover ratio and vice versa, thus a bidirectional relationship between the two variables. The same conclusion was also reached for change in turnover shocks and stock market turnover ratio since their probability values also fall below 1%.

5.4 Chapter Summary.

This Chapter has outlined the stylised facts of the data and the results pertaining to the research goals. Under the stylised facts section, the highlights of the descriptive statistics of the research data were as follows. The Resource 20 index was found to have the highest mean and standard deviation while the Industrial (25) had the lowest mean, and the All-Share index had the lowest standard deviation. Distribution wise, all indices were positively skewed and leptokurtic in the full period analysis. The data was also reviewed using trend analysis to pick out any visual relationships on the change in turnover shocks, illiquidity shocks, stock market turnover ratio and closing price variables. The takeaway here was that across all indices, the clustered spikes observed on the shock measures (ΔTURNSHOCK and LIQUISHOCK) occurred in the same time periods as drastic close price changes entailing some sort of relationship later confirmed by the cointegration tests. The patterns seen on stock market turnover ratio across all indices were quite challenging to decipher and make meaningful observations on.

Furthermore, under the results section, the ARCH and GARCH models estimated were firstly presented. The primary use of these tests was to extract the GARCH model residuals for each return's series and thus proxy volatility for each index. Estimating the GARCH models also revealed that there was volatility persistence in all indices and that past returns did not significantly influence current returns in the period of study. This also proved the weak form efficiency of the indices as discussed in Chapter 2 (Malkiel, 2003). Correlation, VIF and Unit root tests were also used to check the viability of the ARDL models. The correlation and VIF revealed that there were no signs of multicollinearity among the independent variables. On the other hand, the unit root tests showed that change in turnover shocks, illiquidity shocks, conditional volatility and trading volume were all stationary at level terms and thus I (0) for both the All-Share and Panel data tests. Only the exchange rate variable found to be I (1) hence satisfying the ARDL stationarity requirements.

The crux of the Chapter was a review of the ARDL models estimated in pursuit of answering the research goals. Here, the time series ARDL constructed to answer sub goal one showed that a long run relationship was present between All-Share stock market efficiency (SMTURN) and the dependent variables in both the ΔTURNSHOCK and LIQUISHOCK model. It was also concluded from the results that both change in turnover shocks and illiquidity shocks had a positive and long run relationship with stock market turnover ratio. In the short run, change in turnover shocks had a negative and significant relationship while illiquidity shocks had a positive and insignificant relationship with stock market turnover ratio. Next, the PMG panel ARDL was estimated to answer sub goal two of reviewing the impact of liquidity shocks across the three indices. Like the times series ARDL, it was firstly confirmed that a long-run relationship did indeed exist between the liquidity shock proxies and stock market turnover ratio. Thereafter, short run cross sectional results from the PMG model showed that change in turnover shocks had a positive homogenous effect on stock market turnover ratio across the Financial 15, Industrial 25 and Resource 20 indices. For illiquidity shocks, it was shown that a negative homogenous effect on stock market turnover ratio existed only for the Financial 15 and Industrial 25 indices.

To support the ARDL results, the Chapter also looked at the variance decomposition, impulse response functions and Granger Causality methods to review the relationship between liquidity shocks and stock market efficiency from another perspective. From the IRF and VD results, it was highlighted that liquidity shocks have a stronger effect on stock market efficiency than stock market efficiency has on liquidity shocks. Between the two shock measures, change in turnover shocks had a stronger and more consistent impact on stock market turnover ratio as compared to illiquidity shocks. As shown in the ARDL and VD results, illiquidity shocks tend to have insignificant effects on stock market turnover ratio especially in the short run. Lastly, the Granger Causality tests confirmed the bidirectional relationship between liquidity shocks and stock market efficiency. This is true serve for illiquidity shocks and stock market turnover ratio in the All-Share results.

CHAPTER 6

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS.

6.1 Research Summary.

This research was premised on addressing the goals outlined in Section 1.3. The motive to construct these goals came from having noted a gap in the literature and existing empirical evidence that there was no known research on liquidity shocks and stock market efficiency in South Africa. This paper therefore sought to pioneer the research in this area. The main reason for looking at this area of study is the concern raised over stunt financial market development in emerging economies (World Bank, 2016). It was mentioned earlier that stock market development that yields efficiency can lead to overall financial market development. One of the most desired outcomes from this is improved foreign direct investment which boosts economic growth (Otchere, Soumare and Yourougou, 2016).

In an attempt to address the goals of the research, this dissertation looked at existing theories, literature in Financial Economics and existing empirical findings from both domestic and international financial markets. A review of literature helped shed light on the mechanics of the financial market variables of interest such as liquidity, volatility and stock returns. On the other hand, the theories reviewed the Efficient Market Hypothesis which when linked to stock market efficiency gave the realisation that stock markets are for the most part weak form efficient (Malkiel, 2003). Other theories covered include Behavioural Finance and the Adaptive Market Hypothesis to give a more well-rounded outlook on the efficiency of financial markets and thus stock market efficiency in this context.

The existing empirical evidence was analysed across countries and gave a feel of the current and past state of stock market efficiency. An important take away is that it can confidently be noted that developed stock markets are for the most part more efficient than those in emerging economies. Most importantly, existing empirical evidence showed that no prior research had been done investigating the relationship between liquidity shocks and stock market efficiency. Therefore, a priori expectations for the results on the latter relationship presented in Chapter 5 are mainly constructed from inferences made from closely related studies such as the paper by

Bali *et al* (2014) and Jang (2022). The empirical results in Chapter 5 are deduced using mathematical and econometric techniques discussed in Chapter 4. The key findings are discussed below.

6.2 Key Findings.

This section summarises the key findings from Chapters 2, 3 and 5 to see how well they all tie in and best serve in answering the research goals. Chapter 2 looked at the literature and theories surrounding liquidity, liquidity shocks and stock market efficiency (SME). One of the key findings from the literature was that stock markets underreact to liquidity shocks due to market frictions Bali *et al* (2014). In Section 5.3 we notice that liquidity shocks (especially LIQUISHOCK) affect stock market efficiency more significantly in the long run. This could be as a result of this underreaction effect. Another contribution to explain this occurrence was covered in Section 2.5, when Lo (2012) was quoted to stress that time plays an important role when it comes to the efficiency of stock markets. Under the AMH, it is recognised that market participants learn and adapt over time, hence market efficiency can be expected to improve over time. Furthermore, we are introduced to the positive relationship between liquidity and stock market efficiency by Chordia, Roll and Subrahmanyam (2008). Note the latter relationship was confirmed by this research in the time series ARDL for the All-Share variables. It was found that trading volume, a liquidity proxy had a positive short-run and long run relationship with stock market efficiency (SMTURN).

Chapter 3 looked at empirical evidence on liquidity, liquidity shocks and efficiency across countries. As had been discussed in Chapter 2, the positive relationship between liquidity and SME is supported again in the empirical evidence where many researchers including Chung and Hrazdil (2010) concluded that new information was better absorbed in more liquid regimes. Indeed, conditional volatility was found to positively and significantly affect stock market turnover ratio in Section 5.3. Another key finding was that liquidity shocks predict and impact price bubbles (Nneji, 2015). The correlation analysis in Section 5.3 showed significant relationships between the liquidity proxies (LIQUISHOCK and ΔTURNSHOCK) and conditional volatility which is very prevalent during stock price bubbles. When it came to analysing the relationship between volatility and the stock market efficiency, the results were skew towards a positive short-run and long run relationship with stock market turnover ratio. This is not a surprise since a market can be volatile and still be regarded efficient.

Chapter 5 had the sole purpose of answering the goals of the research. This is done using a time series and panel ARDL explained in Section 5.3.4. The study makes use of data collected over a ten-year period (January 2012 to December 2021). The variables under consideration mentioned throughout the research include the dependent variable, stock market efficiency (SMTURN), the liquidity shock proxies (ΔTURNSHOCK and LIQUISHOCK) and the control variables conditional volatility (VOLA), trading volume (VOLU) and the US dollar to South African Rand exchange rate (EXCH). Remember from Chapter 4 that ΔTURNSHOCK can be read as a liquidity shocks and LIQUISHOCK as an illiquidity shocks although together they were referred to as liquidity shock measures for simplicity.

The ARCH and GARCH models showed that all indices depicted volatility persistence and that past returns did not influence current returns making all indices in the study weak form efficient. Adding on, the time series ARDL tested the All-Share index to answer sub goal one. Here it was found that it did not matter where the liquidity shock emanated from, the All-Share stock market turnover ratio would improve in the long run. This means that liquidity shocks make it harder to beat the market in the long run under the EMH premise. In the short run, ΔTURNSHOCK (change in turnover liquidity shocks) decreased the stock market turnover ratio while LIQUISHOCK (illiquidity shocks) showed a positive but statistically insignificant relationship with the All Share stock market turnover ratio. It can thus be said that in the short run, liquidity shocks worsen all share efficiency while illiquidity shocks have no real effects on All- Share efficiency. Another key finding to consider here is the speed of adjustment is quite slow, thus the effects of any shock would persist longer.

Sub goal two was set out to be addressed using the Pooled Mean Group panel ARDL. Here the aim was to determine how the SME for each of the three indices in the panel would be affected by both liquidity shock proxies and if this effect would be homogenous. In the long run, change in turnover shocks and illiquidity shocks significantly affect the panel stock market turnover ratio in opposite directions as expected. However, we are mostly concerned about the PMG cross-sectional short run results. Here it was found that the relationship between the change in turnover shock and stock market efficiency was positively homogenous across the Financial 15, Industrial 25 and Resource 20 indices. Given that the speed of adjustments here are slow, this means that improved efficiency across these indices caused by liquidity shocks persists over time. On the other hand, the relationship between the Amihud illiquidity shock and stock market efficiency was only negatively homogenous for the Financial 15 and Industrial 25 indices only. This means that illiquidity shocks lower efficiency for the Financial 15 and Industrial 25 indices in the short run. However, since the speed of adjustment is moderate here, stock market efficiency returns to equilibrium in good time. Given the above information, the overarching goal is then considered also adequately achieved.

6.3 Recommendations.

6.3.1 Policy Recommendations.

The main concern of the research is how best to improve stock market efficiency especially when faced with liquidity shocks. From the results, it can be noted that no regulation is required in the long run since both liquidity and illiquidity shocks improve the All-Share efficiency significantly. However, in the short run, it was noted that liquidity shocks cause a decline in All Share efficiency. Hence, it would be advised for regulators to focus more on policies that enable absorbing of liquidity shocks in the short run. The same also applies for the Financial 15 and Industrial 25 efficiency levels which dwindle in the face of illiquidity shocks.

6.3.2 Recommendations for further research.

In this section, recommendations for future studies are given. This research only addressed stock markets in South Africa. To get a better, more diversified look at the impact of liquidity shocks on stock market efficiency it would be recommended to include other indices from other countries. This will enable a cross country analysis and comparison of how liquidity shocks impact SME in different settings. Adding on, widening the period of study could also help future studies to get results which capture more trends over time and hence give the results better significance. As noted above, the research made use of two liquidity shock proxies. Given the vast number of liquidity measures, it might benefit future researchers to proxy liquidity shocks by using other liquidity measures. This will broaden the research pool and grow the body of knowledge on the subject.

6.4 Limitations of the study

Note here that the research has made drastic efforts to present a body of work that can be considered free from errors and thus valid. However, it is important to highlight if few areas of concern. As highlighted earlier, the research makes use of two closely related liquidity shocks. This could have limited the scope of the results. Adding on, compared to other Financial Economics research work, the period of study can be considered quite small comparatively. This could have subjected the research to time period bias.

6.5 Conclusion.

The dynamics of financial markets continue to vary over time hence the constant need in improve our body of knowledge about them. This research contributes to this body of knowledge and literature by pioneering the investigation of how liquidity shocks impact stock market efficiency in S.A. In our case since the liquidity shocks proxied influence SME differently, JSE regulatory bodies could now help mitigate or enhance liquidity shocks. The effects being improvement in stock market efficiency and thus financial market development and ultimately economic growth. This section discussed the key findings in relation to the goals of the research. In a nutshell the main findings were as flows. Liquidity shocks do impact capital market efficiency in S.A, change in turnover rate shock and the Amihud illiquidity shock both positively and homogenously impact the All-Share stock market efficiency in the long run. Lastly, the change in turnover rate shock was found to have a positive and significant homogenous impact on the Financial 15, Industrial 25 and Resource 20 indices.

7. REFERENCES

ABHYANKAR, A., GHOSH, D., LEVIN, E. and LIMMACK, R.J., 1997. Bid-ask spreads, trading volume and volatility: Intra-day evidence from the London Stock Exchange. *Journal of Business Finance & Accounting*, *24*(3), pp.343-362.

ADALID, R. and DETKEN, C., 2007. Liquidity shocks and asset price boom/bust cycles.

AHMED, M.F., 2002. Market efficiency in emerging stock markets: the case of Dhaka Stock Exchange (DSE). Savings and Development, pp.49-68.

AITKEN, M. and WINN, R., 1997. What is this thing called liquidity. *Securities Industry Research Center of Asia Pacific Sydney, Australia*.

ALBUQUERQUE, R., SONG, S. and YAO, C., 2020. The price effects of liquidity shocks: A study of the SEC's tick size experiment. *Journal of Financial Economics*, *138*(3), pp.700-724.

AMIHUD, Y. and MENDELSON, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics, 17(2), pp.223-249.

AMIHUD, Y. and MENDELSON, H., 1986. Liquidity and stock returns. *Financial Analysts Journal*, *42*(3), pp.43-48.

AMIHUD, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), pp.31-56.

AMIHUD, Y., HAMEED, A., KANG, W. and ZHANG, H., 2015. The illiquidity premium: International evidence. *Journal of financial economics*, *117*(2), pp.350-368.

AITKEN, M. and COMERTON-FORDE, C., 2003. How should liquidity be measured? Pacific-Basin Finance Journal, 11(1), pp.45-59.

ATKINS, A.B. and DYL, E.A., 1990. Price reversals, bid-ask spreads, and market efficiency. *Journal of Financial and Quantitative Analysis*, *25*(4), pp.535-547.

BAKER, E.B.A., 2021. Crafting Qualitative Research Questions: A Prequel to Design. SAGE Publications.

BALI, T.G. and CAKICI, N., 2008. Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial and Quantitative Analysis*, *43*(1), pp.29-58.

BALI, T.G., PENG, L., SHEN, Y. and TANG, Y., 2014. Liquidity shocks and stock market reactions. *The Review of Financial Studies*, *27*(5), pp.1434-1485.

BARADARANNIA, M.R. and PEAT, M., 2013. Liquidity and expected returns—Evidence from 1926–2008. International Review of Financial Analysis, 29, pp.10-23.

BARADARANNIA, M.R., PEAT, M. and SATCHELL, S., 2015. Liquidity costs, idiosyncratic volatility and expected stock returns. International Review of Financial Analysis, 42, pp.394-406.

BARIVIERA, A.F., 2011. The influence of liquidity on informational efficiency: The case of the Thai Stock Market. *Physica A: Statistical Mechanics and its Applications*, *390*(23-24), pp.4426-4432.

BEDOESKA-SOJKA, B., ECHAUST, K. and JUST, M., 2022. The asymmetry of the Amihud illiquidity measure on the European markets: The evidence from Extreme Value Theory. *Journal of International Financial Markets, Institutions and Money*, *78*, p.101563.

BEKAERT, G., GARCIA, M.G. and HARVEY, C.R., 1995. *The role of capital markets in economic growth*. Chicago: Catalyst Institute

BEKAERT, G. and HARVEY, C.R., 1998. Capital markets: An engine for economic growth. *The Brown Journal of World Affairs*, *5*(1), pp.33-53.

BELTRATTI, A., BORTOLOTTI, B. and CACCAVAIO, M., 2016. Stock market efficiency in China: evidence from the split-share reform. The Quarterly Review of Economics and Finance, 60, pp.125-137.

BEUKES, A., 2010. *The existence of the value premium on the Johannesburg Stock Exchange from 1972 to 2001 and extrapolation as explanation* (Doctoral dissertation, Rhodes University).

BIRAU, F.R., 2012. The impact of Behavioral finance on stock markets. *Annals-Economy Series*, *3*, pp.45-50.

BOLLERSLEV, T. (1986). A generalized least absolute deviation method for parameter estimation of autoregressive signals. IEEE Transactions on Neural Networks, 19(1):107–118

BRASOVEANU, L.O., Dragota, V., Catarama, D. and Semenescu, A., 2008. Correlations between capital market development and economic growth: The case of Romania. *Journal of applied quantitative methods*, *3*(1), pp.64-75.

BRENNAN, M., HUH, S.W. and SUBRAHMANYAM, A., 2013. An analysis of the Amihud illiquidity premium. *The Review of Asset Pricing Studies*, *3*(1), pp.133-176.

BROOKS, C., 2014. *Introductory econometrics for finance*. Cambridge university press.

BUTHELEZI, L., 2022. How the shrinking JSE listings is fuelling offshore investing. [Online]. Available: https://www.news24.com/fin24/economy/how-the-shrinking-jse-listings-is-fuelling-offshore-investing-20220419 [Accessed on 20 April 2022].

CAI, C.X., HUDSON, R. and KEASEY, K., 2004. Intra day bid-ask spreads, trading volume and volatility: recent empirical evidence from the London Stock Exchange. *Journal of Business Finance & Accounting*, *31*(5-6), pp.647-676.

CHAN, K.C., GUP, B.E. and PAN, M.S., 1997. International stock market efficiency and integration: A study of eighteen nations. *Journal of business finance & accounting*, *24*(6), pp.803-813.

CHOI, S.Y., 2021. Analysis of stock market efficiency during crisis periods in the US stock market: Differences between the global financial crisis and COVID-19 pandemic. Physica A: Statistical Mechanics and Its Applications, 574, p.125988.

CHONG, T.T.L., CHENG, S.H.S. and WONG, E.N.Y., 2010. A comparison of stock market efficiency of the BRIC countries. Technology and Investment, 1(4), p.235.

CHORDIA, T., ROLL, R. and SUBRAHMANYAM, A., 2008. Liquidity and market efficiency. Journal of financial Economics, 87(2), pp.249-268.

CHUNG, D. and HRAZDIL, K., 2010. Liquidity and market efficiency: A large sample study. Journal of Banking & Finance, 34(10), pp.2346-2357.

COEN, A. and de La BRUSLERIE, H., 2019. The informational dimensions of the Amihud (2002) illiquidity measure: Evidence from the M&A market. *Finance Research Letters*, *29*, pp.23-29.

COOPER, S.K., GROTH, J.C. and AVERA, W.E., 1985. Liquidity, exchange listing, and common stock performance. *Journal of Economics and Business*, *37*(1), pp.19-33.

CROCKETT, A., 2008. Market liquidity and financial stability. *Financial Stability Review*, *11*, pp.13-17.

DANIEL, K., HIRSHLEFER, D. and SUBRAHMANYAM, A., 1998. Investor psychology and security market under-and overreactions. *the Journal of Finance*, *53*(6), pp.1839-1885.

Dang, T.L., MOSHIRIAN, F., SUBRAHMANYAM, A. and ZHANG, B., 2014. Global Financial Crisis, liquidity shocks and global financial stability. *CIFR Paper*, (014).

DARRAT, A.F., 1987. Money and stock prices in West Germany and the United Kingdom: Is the stock market efficient? Quarterly Journal of Business and Economics, pp.20-35.

DHANKAR, R.S. and SHANKAR, D., 2016. Relevance and evolution of adaptive markets hypothesis: a review. *Journal of Indian Business Research*, *8*(3), pp.166-179.

DONAUBAUER, J., NEUMAYER, E. and NUNNENKAMP, P., 2020. Financial market development in host and source countries and their effects on bilateral foreign direct investment. *The World Economy*, *43*(3), pp.534-556.

DU, W., 2021. News and market efficiency in the Japanese stock market. Journal of Behavioral Finance, 22(3), pp.306-319.

ELTON, E.J., GRUBER, M.J., BROWN, S.J. and GOETZMANN, W.N., 2009. *Modern portfolio theory and investment analysis*. John Wiley & Sons.

ENGLE, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, 50(4): 987

ENGLE, R. F., & GRANGER, C. W. J. (1987). Co-integration and error correction: representation, estimation, and testing. 55 (2): 251-276

FAKHRY, B., 2016. A literature review of the efficient market hypothesis. *Turkish Economic Review*, *3*(3), pp.431-442.

FAMA, E.F., 1965. The behavior of stock-market prices. *The journal of Business*, *38*(1), pp.34-105.

FAMA, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), pp.383-417

FILIS, G., 2006. Testing for market efficiency in emerging markets: Evidence from the Athens Stock Exchange. Journal of Emerging Market Finance, 5(2), pp.121-133.

FOX, N.J., 2008. Post-positivism. The SAGE encyclopaedia of qualitative research methods, 2, pp.659-664.

FUSTHANE, O. and KAPINGURA, F.M., 2017. Weak form market efficiency of the johannesburg stock exchange: pre, during and post the 2008 global financial crisis. *Journal of Economics and Behavioral Studies*, *9*(5 (J)), pp.29-42.

GIMBA, V.K., 2012. Testing the weak-form efficiency market hypothesis: Evidence from Nigerian stock market. CBN Journal of Applied Statistics, 3(1), pp.117-136.

GIRARD, E. and BISWAS, R., 2007. Trading volume and market volatility: Developed versus emerging stock markets. *Financial Review*, *42*(3), pp.429-459.

GOYAL, A. and SANTA-CLARA, P., 2003. Idiosyncratic risk matters! *The journal of finance*, *58*(3), pp.975-1007.

GOYENKO, R.Y., HOLDEN, C.W. and TRZCINKA, C.A., 2009. Do liquidity measures measure liquidity?. *Journal of financial Economics*, *92*(2), pp.153-181.

GOYENKO, R.Y. and UKHOV, A.D., 2009. Stock and bond market liquidity: A long-run empirical analysis. *Journal of Financial and Quantitative Analysis*, *44*(1), pp.189-212.

GRANGER, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica. 37 (3): 424-438

GUNAWAN, G. and HENDRAWATY, E., 2018. Stock Liquidity and Market Capitalization: Investment Challenges in Indonesian Capital Markets. *SSRG International Journal of Economics Management Studies (SSRG–IJEMS)–Volume 5 Issue 11–November 2018*, *5*(11)

GWILYM, O. and THOMAS, S., 2002. An empirical comparison of quoted and implied bid–ask spreads on futures contracts. *Journal of International Financial Markets, Institutions and Money*, *12*(1), pp.81-99.

HAGSTROMER, B., 2021. Bias in the effective bid-ask spread. Journal of Financial Economics, 142(1), pp.314-337.

HAN, Y. and HUANG, Z., 2022. Liquidity Shocks and the Firm Fundamentals. *Available at SSRN 4143493*.

HASSAN, M.K., ISLAM, M.A. and BASHER, S.A., 2000. Market efficiency, time-varying volatility and equity returns in Bangladesh stock market. Applied Financial Economics, 6.

HEYMANS, A. and SANTANA, L., 2018. How efficient is the Johannesburg Stock Exchange really?. *South African Journal of Economic and Management Sciences*, *21*(1), pp.1-14.

HUMPE, A. and McMILLAN, D.G., 2020. Macroeconomic variables and long-term stock market performance. A panel ARDL cointegration approach for G7 countries. *Cogent Economics & Finance*, *8*(1), p.1816257.

IM, K. S., HASHEM PESARAN, M., & SHIN, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics. 115: 53–74

ITO, M. and SUGIYAMA, S., 2009. Measuring the degree of time varying market inefficiency. *Economics Letters*, *103*(1), pp.62-64.

ITO, M., NODA, A. and WADA, T., 2016. The evolution of stock market efficiency in the US: a non-Bayesian time-varying model approach. Applied Economics, 48(7), pp.621-635.

IWANANGA, Y. and HIROSE, T., 2022. Liquidity shock and stock returns in the Japanese equity market. *Pacific-Basin Finance Journal*, *75*, p.101849.

JANG, J., 2022. What Drives Stock Market Underreaction to Liquidity Shocks? Evidence from Korea. *Asia-Pacific Journal of Financial Studies*, *51*(1), pp.44-80.

KARPOFF, J.M., 1987. The relation between price changes and trading volume: A survey. *Journal of Financial and quantitative Analysis*, *22*(1), pp.109-126.

KEMME, D.M., McLNISH, T.H. and ZHANG, J., 2022. Market fairness and efficiency: Evidence from the Tokyo Stock Exchange. Journal of Banking & Finance, 134, p.106309.

KENDALL, M.G. and Hill, A.B., 1953. The analysis of economic time-series-part i: Prices. *Journal of the Royal Statistical Society. Series A (General)*, *116*(1), pp.11-34

KIM, J., 2013. How does stock market liquidity forecast economic growth? *European Journal of Business and Management*, *5*(31), pp.155-164

KIRAN, S., 2019. Analysis of Stock Market Efficiency in Emerging Markets: Evidence from BRICS. Romanian Economic Journal.

KIVUNJA, C. and KUYINI, A.B., 2017. Understanding and applying research paradigms in educational contexts. *International Journal of higher education*, *6*(5), pp.26-41.

KOLAPO, F.T. and ADARAMOLA, A.O., 2012. The impact of the Nigerian capital market on economic growth (1990-2010). *International Journal of Developing Societies*, *1*(1), pp.11-19.

KUMAR, G. and MISRA, A.K., 2015. Closer view at the stock market liquidity: A literature review. *Asian Journal of Finance and accounting*, *7*(2), pp.35-57.

KUNJAL, D., 2021. The impact of COVID-19 on stock market liquidity: Evidence from the Johannesburg Stock Exchange. *African Review of Economics and Finance*, *13*(2), pp.104-123.

LE, H. and GREGORIOU, A., 2020. How do you capture liquidity? A review of the literature on low-frequency stock liquidity. Journal of Economic Surveys, 34(5), pp.1170-1186.

LEVIN, A., LIN, C. F., & JAMES CHU, C. S. (2002). Unit root tests in panel data: 90 asymptotic and finite-sample properties. Journal of Econometrics. 108: 1-24.

LEVINE, R. and ZERVOS, S., 1996. Stock market development and long-run growth. *The world bank economic review*, *10*(2), pp.323-339

LIM, K.P. and BROOKS, R., 2011. The evolution of stock market efficiency over time: A survey of the empirical literature. *Journal of economic surveys*, *25*(1), pp.69-108.

LIM, T.C., HUANG, W., YUN, J.L.X. and ZHAO, D., 2013. Has stock market efficiency improved? Evidence from China. Journal of Finance & Economics, 1(1), pp.1-9.

LIU, T., 2011. Market efficiency in China stock market and Hong Kong stock market. International research journal of finance and economics, 76, pp.128-137.

LO, A.W., 2004. The adaptive markets hypothesis. *The Journal of Portfolio Management*, *30*(5), pp.15-29.

LO, A.W., 2012. Adaptive markets and the new world order (corrected May 2012). *Financial Analysts Journal*, *68*(2), pp.18-29.

LOU, X. and SHU, T., 2017. Price impact or trading volume: Why is the Amihud (2002) measure priced?. *The Review of Financial Studies*, *30*(12), pp.4481-4520.

LOUKIL, N., ZAYANI, M.B. and OMRI, A., 2010. Impact of liquidity on stock returns: an empirical investigation of the Tunisian stock market. *Macroeconomics and Finance in Emerging Market Economies*, *3*(2), pp.261-283.

MA, R., ANDERSON, H.D. and MARSHALL, B.R., 2018. Market volatility, liquidity shocks, and stock returns: Worldwide evidence. *Pacific-Basin finance journal*, *49*, pp.164-199.

MADDALA, G. S., & WU, S. (1999). A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and Statistics. 61: 631-652.

MAGNUSSON, M. and WYDICK, B., 2002. How efficient are Africa's emerging stock markets? Journal of Development Studies, 38(4), pp.141-156.

MALAGON, J., MORENO, D. and RODRIGUEZ, R., 2018. Idiosyncratic volatility, conditional liquidity and stock returns. *International Review of Economics & Finance*, *53*, pp.118-132.

MALKIEL, B.G. and XU, Y., 2002. Idiosyncratic risk and security returns. *University of Texas at Dallas (November 2002)*.

MALKIEL, B.G., 2003. The efficient market hypothesis and its critics. *Journal of economic perspectives*, *17*(1), pp.59-82.

MAROZVA, G., 2019. Liquidity and stock returns: New evidence from Johannesburg Stock Exchange. The Journal of Developing Areas, 53(2).

MILIONIS, A.E. and MOSCHOS, D., 2000. On the validity of the weak–form efficient markets hypothesis applied to the London stock exchange: comment. Applied Economics Letters, 7(7), pp.419-421.

MOBAREK, A., MOLLAH, A.S. and BHUYAN, R., 2008. Market efficiency in emerging stock market: Evidence from Bangladesh. Journal of emerging market finance, 7(1), pp.17-41.

MUKHERJI, R., 2015. Stock market efficiency in developing economies. Margin: The Journal of Applied Economic Research, 9(4), pp.402-429.

MULAMU, M., 2021. Exchange rate volatility and the returns on diversified South African investment portfolios.

MURAGU, K., 1990. Stock market efficiency in developing countries: a case study of the Nairobi stock exchange (Doctoral dissertation, University of Glasgow).

MUSTAFA, K. and NISHAT, M., 2007. Testing for market efficiency in emerging markets: A case study of the Karachi stock market. The Lahore Journal of Economics, 12(1), pp.119-140.

NAGAYASU, J., 2003. The efficiency of the Japanese equity market. In The Japanese Finance: Corporate Finance and Capital Markets in.... Emerald Group Publishing Limited.

NAIK, P. and REDDY, Y.V., 2021. Determinants of stock market liquidity–a macroeconomic perspective. Macroeconomics and Finance in Emerging Market Economies, pp.1-21.

NARASIMHAN, M.S. and KALRA, S., 2014. The impact of derivative trading on the liquidity of stocks. *Vikalpa*, *39*(3), pp.51-66

NARAYAN, P.K. and ZHENG, X., 2011. The relationship between liquidity and returns on the Chinese stock market. Journal of Asian Economics, 22(3), pp.259-266.

NASEER, M. and BIN TARIQ, D., 2015. The efficient market hypothesis: A critical review of the literature. *The IUP Journal of Financial Risk Management*, *12*(4), pp.48-63.

NAZIMA, E., 2011. Exchange rate volatility and foreign direct investment (FDI) behavior in Pakistan: A time series analysis with auto regressive distributed lag (ARDL) application. African Journal of Business Management, 5(29), pp.11656-11661.

NKORO, E., & UKO, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. Journal of Statistical and Econometric Methods. 5(4): 63–91.

NNEJI, O., 2015. Liquidity shocks and stock bubbles. *Journal of International Financial Markets, Institutions and Money*, *35*, pp.132-146.

NTIM, C.G., OPONG, K.K., DANBOLT, J. and DEWATOR, F.S., 2011. Testing the weak-form efficiency in African stock markets. Managerial Finance.

NURUNNABI, M., 2012. Testing weak-form efficiency of emerging economies: a critical review of literature. Journal of Business Economics and Management, 13(1), pp.167-188.

OTCHERE, I., SOUMARE, I. and YOUROUGOU, P., 2016. FDI and financial market development in Africa. *The World Economy*, *39*(5), pp.651-678.

OOI, J.T., WANG, J. and WEBB, J.R., 2009. Idiosyncratic risk and REIT returns. *The Journal of Real Estate Finance and Economics*, *38*(4), pp.420-442.

PANHWAR, A.H., ANSARI, S. and SHAH, A.A., 2017. Post-positivism: An effective paradigm for social and educational research. International Research Journal of Arts & Humanities (IRJAH), 45(45).

PENG, L. and XIONG, W., 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), pp.563-602.

PESARAN, M. H., & PESARAN, B. (1997). Working with Microfit 4.0: Interactive 93 Econometric Analysis. Oxford: Oxford University Press.

PESARAN, H. M., & SHIN, Y. (1995). Long-run structural modelling. Report. Cambridge, England: Dept of Applied Economics, University of Cambridge

PESARAN, M.H., SHIN, Y. and SMITH, R.P., 1999. Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American statistical Association*, *94*(446), pp.621-634.

POSHAKWALE, S., 1996. Evidence on weak form efficiency and day of the week effect in the Indian stock market. Finance India, 10(3), pp.605-616.

RABBANI, S., KAMAL, N. and SALIM, M., 2013. Testing the weak-form efficiency of the stock market: Pakistan as an emerging economy. Journal of Basic and Applied Scientific Research, 3(4), pp.136-142.

REJEB, A.B. and BOUGHRARA, A., 2013. Financial liberalization and stock markets efficiency: New evidence from emerging economies. Emerging markets review, 17, pp.186-208.

RITTER, J.R., 2003. Behavioral finance. *Pacific-Basin finance journal*, *11*(4), pp.429-437.

ROBINSON, J., 2005. Stock price behaviour in emerging markets: Tests for weak form market efficiency on the Jamaica Stock Exchange. Social and Economic Studies, pp.51-69.

RODRIGUEZ, E., AGUILAR-CORNEJO, M., FEMAT, R. and ALVAREZ-RAMIREZ, J., 2014. US stock market efficiency over weekly, monthly, quarterly and yearly time scales. Physica A: Statistical Mechanics and its Applications, 413, pp.554-564.

ROSCH, D., 2015. *Market Efficiency and Liquidity* (No. EPS-2015-353-FA).

ROUNAGHI, M.M. and ZADEH, F.N., 2016. Investigation of market efficiency and financial stability between S&P 500 and London stock exchange: monthly and yearly forecasting of time series stock returns using ARMA model. Physica A: Statistical Mechanics and its Applications, 456, pp.10-21.

SAMARATUNGA, D., 2009. Stock market efficiency and integration: a study of eight economies in the Asia-Pacific region. Staff Studies, 38(1).

SANTOSO, W., HARUN, C.A., HIDAYAT, T. and WONIDA, H., 2010. MarketLiquidityRisk as an Indicator of Financial Stability: The Case of Indonesia. *Bank of Indonesia*.

SARR, A. and LYBEK, T., 2002. Measuring liquidity in financial markets. Available at SSRN 880932.

SETH, N. and SHARMA, A.K., 2015. International stock market efficiency and integration: evidence from Asian and US markets. Journal of Advances in Management Research.

SHARMA, J.L. and KENNEDY, R.E., 1977. A comparative analysis of stock price behavior on the Bombay, London, and New York stock exchanges. Journal of Financial and Quantitative Analysis, 12(3), pp.391-413.

SHILLER, R.J., 2003. From efficient markets theory to behavioral finance. *Journal of economic perspectives*, *17*(1), pp.83-104.

SHRESTHA, M.B. and BHATTA, G.R., 2018. Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science*, *4*(2), pp.71-89.

SIMON, H.A., 1955. A behavioral model of rational choice. *The quarterly journal of economics*, pp.99-118.

SMITH, G., 2008. Liquidity and the informational efficiency of African stock markets. South African Journal of Economics, 76(2), pp.161-175.

SMITH, G. and DYAKOVA, A., 2014. African Stock Markets: Efficiency and Relative Predictability. South African journal of economics, 82(2), pp.258-275.

STEFANOVSKI, M. and RASIN, E., 2013. Effects of liquidity on idiosyncratic risk.

STERENCZAK, S., 2021. Conditional stock liquidity premium: is Warsaw stock exchange different? *Studies in Economics and Finance*.

TETLOCK, P.C., 2007. Does liquidity affect securities market efficiency. *University of Texas*.

THE GLOBAL ECONOMY. (2022). Stock market turnover ratio - Country Rankings. [Online]. Available: https://www.theglobaleconomy.com/rankings/stock_market_turnover_ratio/ [Accessed on 08 December 2022].

TSUTSUI, Y. and HIRAYAMA, K., 2004. Market efficiency and international linkage of stock prices: An analysis with high-frequency data.

WORLD BANK, 2016. *Financial Development.* [Online]. Available: https://www.worldbank.org/en/publication/gfdr/gfdr-2016/background/financial-development [Accessed on 20 April 2022].

WORLD BANK GROUP, 2020. *Capital Markets Development: A Primer for Policymakers*. World Bank.

WORTHINGTON, A. and HIGGS, H., 2004. Random walks and market efficiency in European equity markets. The Global Journal of Finance and Economics, 1(1), pp.59-78.

WUYTS, G., 2007. Stock market liquidity: determinants and implications. Review of Business and Economics, (2), pp.279-316.

YARTEY, C.A., 2008. The determinants of stock market development in emerging economies: Is South Africa different?

YILMAZ, K., 2001. Market development and efficiency in emerging stock markets. Available at SSRN 280889.

8.APPENDICES.

Appendix A.

ARCH effects for the All-Share index

Heteroskedasticity Test: ARCH

F-statistic	39.47766	Prob. F(1,2493)	0.0000
Obs*R-squared	38.89344	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/16/23 Time: 16:59
Sample (adjusted): 4 2498
Included observations: 2495 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.86E-05	8.40E-06	11.74329	0.0000
RESID^2(-1)	0.124854	0.019871	6.283125	0.0000

R-squared	0.015589	Mean dependent var	0.000113
Adjusted R-squared	0.015194	S.D. dependent var	0.000407
S.E. of regression	0.000404	Akaike info criterion	-12.78837
Sum squared resid	0.000407	Schwarz criterion	-12.78371
Log likelihood	15955.49	Hannan-Quinn criter.	-12.78668
F-statistic	39.47766	Durbin-Watson stat	2.127568
Prob(F-statistic)	0.000000		

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

ARCH effects for the Financial 15 index

Heteroskedasticity Test: ARCH

F-statistic	268.4967	Prob. F(1,2493)	0.0000
Obs*R-squared	242.5856	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/16/23 Time: 15:44
Sample (adjusted): 1/06/2012 12/30/2021
Included observations: 2495 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000152	1.66E-05	9.192768	0.0000
RESID^2(-1)	0.311816	0.019030	16.38587	0.0000

R-squared	0.097229	Mean dependent var	0.000222
Adjusted R-squared	0.096867	S.D. dependent var	0.000843
S.E. of regression	0.000801	Akaike info criterion	-11.41996
Sum squared resid	0.001601	Schwarz criterion	-11.41530
Log likelihood	14248.40	Hannan-Quinn criter.	-11.41827
F-statistic	268.4967	Durbin-Watson stat	2.214760
Prob(F-statistic)	0.000000		

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

ARCH effects for the Industrial 25 index

Heteroskedasticity Test: ARCH

F-statistic	32.50847	Prob. F(1,2494)	0.0000
Obs*R-squared	32.11592	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/16/23 Time: 16:17
Sample (adjusted): 1/05/2012 12/30/2021
Included observations: 2496 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000112	6.99E-06	15.99012	0.0000
RESID^2(-1)	0.113436	0.019895	5.701620	0.0000

R-squared	0.012867	Mean dependent var	0.000126
Adjusted R-squared	0.012471	S.D. dependent var	0.000328
S.E. of regression	0.000326	Akaike info criterion	-13.22001
Sum squared resid	0.000265	Schwarz criterion	-13.21534
Log likelihood	16500.57	Hannan-Quinn criter.	-13.21832
F-statistic	32.50847	Durbin-Watson stat	2.081851
Prob(F-statistic)	0.000000		

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

ARCH effects for the Resource 25 index.

Heteroskedasticity Test: ARCH

F-statistic	16.60871	Prob. F(1,2494)	0.0000
Obs*R-squared	16.51207	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/16/23 Time: 16:39
Sample (adjusted): 1/05/2012 12/30/2021
Included observations: 2496 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000275	1.95E-05	14.11530	0.0000
RESID^2(-1)	0.081337	0.019958	4.075378	0.0000

R-squared	0.006615	Mean dependent var	0.000299
Adjusted R-squared	0.006217	S.D. dependent var	0.000929
S.E. of regression	0.000926	Akaike info criterion	-11.13026
Sum squared resid	0.002139	Schwarz criterion	-11.12560
Log likelihood	13892.57	Hannan-Quinn criter.	-11.12857
F-statistic	16.60871	Durbin-Watson stat	2.039291
Prob(F-statistic)	0.000047		

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

Appendix B

Bounds Test results for the time series ARDL with LIQUISHOCK.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	22.65568	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	2254	Finite Sample: n=80		
		10%	2.303	3.22
		5%	2.688	3.698
		1%	3.602	4.787

Source: EViews Output: Data from Thomson Reuters (2022) and IRESS (2022)

Bounds Test results for the time series ARDL with ΔTURNSHOCK.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	20.90356	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	2254	Finite Sample: n=80		
		10%	2.303	3.22
		5%	2.688	3.698
		1%	3.602	4.787

Source: EViews Output: Data from Thomson Reuters (2022) and IRESS (2022)

Appendix C.

Variance Decomposition results between the All Share SMTURN and LIQUISHOCK/ ΔTURNSHOCK (seen here as _TURNOVER)

Variance Decomposition of SMTURN: Period	S.E.	SMTURN	LIQUISHOCK	Variance Decomposition of SMTURN: Period	S.E.	SMTURN	_TURRNOVER
1	9.53E-06	100.0000	0.000000	1	6.84E-06	100.0000	0.000000
2	1.05E-05	99.67841	0.321591	2	9.70E-06	56.42200	43.57800
3	1.14E-05	99.59684	0.403160	3	1.07E-05	55.10298	44.89702
4	1.29E-05	99.36893	0.631074	4	1.17E-05	58.62630	41.37370
5	1.39E-05	99.24651	0.753486	5	1.24E-05	59.32702	40.67298
6	1.48E-05	99.13974	0.860256	6	1.34E-05	58.12434	41.87566
7	1.58E-05	99.04082	0.959178	7	1.42E-05	58.11622	41.88378
8	1.66E-05	98.96921	1.030795	8	1.49E-05	58.31661	41.68339
9	1.74E-05	98.90629	1.093705	9	1.56E-05	58.48318	41.51682
10	1.82E-05	98.85339	1.146614	10	1.63E-05	58.42750	41.57250

Variance Decomposition of LIQUISHOCK: Period	S.E.	SMTURN	LIQUISHOCK	Variance Decomposition of _TURRNOVER: Period	S.E.	SMTURN	_TURRNOVER
1	464960.6	0.395924	99.60408	1	7981706.	0.464311	99.53569
2	469352.6	0.423444	99.57656	2	8944378.	0.539173	99.46083
3	476217.6	0.478850	99.52115	3	8978850.	0.537432	99.46257
4	476885.5	0.477852	99.52215	4	8978903.	0.538245	99.46175
5	476949.9	0.501056	99.49894	5	9065743.	0.531493	99.46851
6	477112.1	0.507925	99.49207	6	9075747.	0.533451	99.46655
7	477120.4	0.510334	99.48967	7	9078096.	0.533708	99.46629
8	477144.0	0.517832	99.48217	8	9078122.	0.533828	99.46617
9	477157.4	0.522496	99.47750	9	9080384.	0.533562	99.46644
10	477168.3	0.526845	99.47316	10	9080437.	0.533856	99.46614

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: SMTURN LIQUISHOCK

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: SMTURN _TURRNOVER

Source: EViews output: Data from Thompson Reuters (2022) and IRESS (2022)

Variance Decomposition results between Panel SMTURN and LIQUISHOCK/ ΔTURNSHOCK (seen here as _TURNOVER)

Variance Decomposition of SMTURN:

Period	S.E.	SMTURN	LIQUISHOCK
1	1.50E-05	100.0000	0.000000
2	1.66E-05	99.57948	0.420517
3	1.78E-05	99.62076	0.379237
4	2.01E-05	99.67531	0.324690
5	2.17E-05	99.65815	0.341855
6	2.30E-05	99.66972	0.330283
7	2.45E-05	99.68132	0.318675
8	2.58E-05	99.68352	0.316477
9	2.70E-05	99.68835	0.311651
10	2.82E-05	99.69277	0.307230

Variance Decomposition of LIQUISHOCK:

Period	S.E.	SMTURN	LIQUISHOCK
1	168137.8	3.321332	96.67867
2	168936.6	3.567910	96.43209
3	169817.8	3.644294	96.35571
4	169904.9	3.737412	96.26259
5	169930.5	3.763349	96.23665
6	169930.6	3.763392	96.23661
7	169933.4	3.766475	96.23353
8	169933.8	3.766922	96.23308
9	169933.8	3.766922	96.23308
10	169934.0	3.767131	96.23287

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: SMTURN LIQUISHOCK

Variance Decomposition of SMTURN:

Period	S.E.	SMTURN	_TURNOVER
1	1.37E-05	100.0000	0.000000
2	1.62E-05	86.65475	13.34525
3	1.74E-05	85.96624	14.03376
4	1.96E-05	87.62650	12.37350
5	2.10E-05	88.09322	11.90678
6	2.23E-05	87.56379	12.43621
7	2.37E-05	87.61522	12.38478
8	2.50E-05	87.69157	12.30843
9	2.62E-05	87.77425	12.22575
10	2.73E-05	87.77903	12.22097

Variance Decomposition of _TURNOVER:

Period	S.E.	SMTURN	_TURNOVER
1	3102370.	0.108481	99.89152
2	3432434.	0.091051	99.90895
3	3451100.	0.199271	99.80073
4	3453310.	0.244244	99.75576
5	3491330.	0.241271	99.75873
6	3493749.	0.244326	99.75567
7	3494795.	0.244536	99.75546
8	3495058.	0.245147	99.75485
9	3495941.	0.245029	99.75497
10	3495942.	0.245029	99.75497

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: SMTURN _TURNOVER

Appendix D.

Variance Inflation Factors for All Share Variables with LIQUISHOCK.

Variance Inflation Factors
Date: 02/13/23 Time: 16:53
Sample: 1/03/2012 12/31/2021
Included observations: 2436

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
LIQUISHOCK	2.07E-26	1.010026	1.010003
EXCH	9.85E-16	36.55853	1.165662
VOLA	4.27E-11	1.010797	1.010372
VOLU	4.27E-31	6.659946	1.166723
C	1.49E-13	31.37738	NA

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)

Variance Inflation Factors for All Share Variables with ΔTURNSHOCK (seen here as _TURNOVER)

Variance Inflation Factors
Date: 02/13/23 Time: 17:00
Sample: 1/03/2012 12/31/2021
Included observations: 2436

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
_TURNOVER	7.23E-29	1.186261	1.185332
EXCH	1.00E-15	37.31398	1.189750
VOLA	4.23E-11	1.002817	1.002396
VOLU	5.04E-31	7.871191	1.378915
C	1.49E-13	31.39045	NA

Source: EViews Output. Data from Thomson Reuters (2022) and IRESS (2022)