LIQUIDITY AND THE CONVERGENCE TO MARKET EFFICIENCY

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NICARA YOUNG
567597

MASTER OF COMMERCE (FINANCE)

in the

FINANCE DIVISION,

SCHOOL OF ECONOMIC AND BUSINESS SCIENCES

at the

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Supervisor: PROF. CHRISTO AURET

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DECLARATION

I, Nicara Young, declare that this research report is my own unaided work. It is submitted in partial fulfilment of the requirements for the degree of Master of Commerce in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at this or any other university.

Nicara Young

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ABSTRACT

The aim of this study is to investigate the relationship between market liquidity changes on the Johannesburg Stock Exchange (JSE), and the market's degree of efficiency. Market efficiency is characterised in terms of two philosophies: Fama's (1970) Efficient Markets Hypothesis, and Shiller's (1981; 2003) informational efficiency designation. Efficiency was tested using measures of return predictability, a random walk benchmark, and price volatility; liquidity was measured using market turnover. The tests were conducted on JSE Top 40 shares across three regimes, spanning January 2012 – June 2016. The regimes are demarcated by two structural breaks in the JSE's microstructure: the 2012 trading platform upgrade, and the 2014 colocation centre launch. The results show that past order imbalances are a significant predictor of daily returns, although the significance of this predictability has dissipated over time. Return predictability is not influenced by liquidity. In fact, there is evidence that illiquidity weakens return predictability. Prices were closer to random walk benchmarks during the third regime. In consideration of informational efficiency, during the latter two regimes price volatility is greater during trading versus non-trading hours. This is coupled with an emergence of nonlinear return dependence, which is indicative of greater mispricing. Thus, over the three regimes, market efficiency improved in the sense of the EMH, but informational efficiency deteriorated. The study contributes to the field by: introducing an inverse measure of market efficiency; providing insight into the measure's time variation and relation to liquidity; and demonstrating that market efficiency tests should incorporate its dual meanings, enabling richer understanding of their intersection.

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1 INTRODUCTION

The organised stock market is one of the most ingenious constructs born of modern capitalism. It allows corporations to raise capital by issuing ownership stakes in their businesses. It facilitates trade in these claims, with the market maker ensuring no direct negotiation between buyers and sellers is necessary. The financial market's effectiveness in performing both of these functions depends critically on two qualities: efficiency and liquidity.

1.1 MARKET EFFICIENCY

Any product adept at serving its purpose can be described as efficient. In the case of financial markets, efficiency is two-pronged. Efficiency may describe the inability to earn returns on assets in excess of expectations, after adjusting for the risk taken on. It may also describe a rational expectations paradigm in which asset prices are a perfect reflection of their true values. As will be reasoned in what follows, these two concepts are far from equivalent.

The much-lauded and equally challenged Efficient Markets Hypothesis (EMH) of Fama (1970) is attuned to the first arm of 'two-pronged efficiency': an efficient capital market is one that is sufficiently competitive so that investors cannot expect to realise abnormal (or arbitrage) profits from trading strategies, where an abnormal profit is defined as a return in excess of what is expected based on the risk of an asset or portfolio. In more formal terms, Fama's (1970) idea of efficiency is the speed and degree to which prices adjust to fully reflect all available, relevant information. All that is pertinent to the computation of the price has already been impounded into its observed value today. As new information arrives randomly, if prices adjust instantly to the new information then price changes should be random. The natural implication of this is a lack of asset return predictability from past prices or information. An extension of the 'fair game' efficient markets model is that the path of past and future prices follows a 'random walk': price changes are independent and identically distributed (i.i.d.). The EMH and random walk theory are not necessarily interchangeable ideas: although statistically significant non-random behaviour is sufficient to reject the random walk hypothesis, the EMH can only be rejected if it can be shown that the statistical non-randomness can be used to beat the market. However, non-randomness is still relevant to tests of market efficiency, as the less non-randomness, the lower the chance of finding trading strategies that yield superior returns. See Strebel (1977).

Importantly, the EMH does not completely rule out minor instances of price predictability. What it does maintain is that deviations from efficiency, such as return predictability or non-randomness, are traded away so quickly that, on average, it is not possible to earn an arbitrage profit.

Fama's (1970) description of market efficiency is quite distinct from that of Shiller (1981; 2003), who emphasises the conformity of prices to fundamental values as a designation of efficiency: 'The idea [is] that speculative asset prices such as stock prices always incorporate the best information about fundamental values and that prices change only because of good, sensible information' (Shiller, 2003, p. 83). How well financial asset prices follow fundamental values will depend on market consensus on the value of the asset, but as will be discussed later, market consensus on value can be disrupted by investor biases and by asymmetric information. If investors exhibit irrational behaviour such as herding, overreaction or under-reaction, this can generate divergence of asset prices from true values. Similarly, if there are market participants with superior information, but who are not able to trade on this information, then the market price cannot reflect the true, fundamental value.

In order to avoid possible confusion due to the dual use of the term 'efficiency', it will henceforth be qualified. When referring to the Fama (1970) description, 'the EMH', 'random walk theory' or 'lack of return predictability' will be used. The Shiller (1981; 2003) usage can be referred to as 'informational efficiency', 'price informativeness', 'transparency', or 'fundamental value'.

The important question is why academics and practitioners should care about market efficiency in the sense of both Fama (1970) and Shiller (1981; 2003). The validity of Fama's (1970) EMH has for decades been the subject of heated debate in the academic literature, but it cannot be denied that its central tenet underpins almost every aspect of finance theory. Accordingly, knowledge of the drivers and dynamics of the EMH, and whether it can be reconciled with Shiller's (1981; 2003) description of efficiency, should be welcomed by the academic community. The EMH has direct implications for market participants when they transact. Investors who pursue active portfolio management rely on the hope of beating the market: for instance, the predictability of stock returns affects the profitability of technical trading strategies, and the ability to earn returns in excess of what would be expected according to an asset’s risk. Price informativeness (accurate pricing of fundamentals) is an even more important consideration for corporate management than it is for academics. Firms rely on market transparency when obtaining access to capital and calculating its cost, when valuing corporate takeover deals, and when determining manager compensation.

1.2 MARKET LIQUIDITY

A second characteristic of a well-functioning market is the liquidity of its traded assets. A liquid asset is one which can be promptly traded or converted into cash, at a low cost of transaction and without having to bear undue sacrifice on the price. Liu (2006) identifies four dimensions of liquidity – trading speed, trading quantity (turnover or volume), trading cost, and price impact. ‘Undue sacrifice on the price’ is a trading cost that describes having to purchase the asset at a higher price and sell at a lower price than if it were more liquid. ‘Price impact’ is the effect of trade on the future price, as a consequence of the asset’s illiquidity. The sources of illiquidity are wide-ranging: exogenous transaction costs such as brokerage fees; demand pressure and inventory risk; private information about share fundamentals and/ or order flow; and search frictions associated with locating a trading partner and negotiating a price in an imperfectly competitive context (Amihud, Mendelson & Pedersen, 2005).

A developing body of literature speaks of the ‘liquidity premium’, or the return compensation required by investors for holding an illiquid asset (Acharya & Pedersen, 2005; Amihud, 2002; Liu, 2006; McClelland, 2014). Capital markets aid in the trading of assets, but the constituent assets can, and do, vary in the degree of trading friction and transaction costs in the cross-section and across time. The liquidity or ease of trade of a company’s shares is influenced by the nuances of the firm, such as its size and investors’ perceptions of the riskiness of the business. For example, there tends to be a wider bid-ask spread (a direct measure of transaction cost) for smaller and riskier firms. More than that, the structure of the market on which the share is listed can impact its ease of trade (O’Hara, 2015). Research of market microstructure theory is pivotal to understanding both asset pricing and the process by which markets become efficient (O’Hara, 1997), but the South African literature has been relatively silent on how asset returns and price formation are affected by the market which defines the setting to these phenomena.

Market liquidity is inextricably tied to market microstructure. Chordia, Roll and Subrahmanyam (2001) as well as Chordia, Sarkar and Subrahmanyam (2005) (on raw data) documented that successive reductions in the minimum tick size of U.S. stocks were accompanied by exogenous decreases in bid-ask spreads. Muranaga (1999) studied dynamic aspects of market liquidity on the Tokyo Stock Exchange. Besides trade frequency being found to be positively correlated with indicators of static and dynamic market liquidity, the paper uses an event study to conclude that a reduction in tick size of the Japanese exchange in 1998 resulted in decreased bid-ask spreads and price volatility, and increased trade frequency, implying a likely improvement in market liquidity and efficiency.

The benefits of liquid secondary markets cannot be overstated: investors value liquidity, and, *ceteris paribus*, will accept lower yields on securities that trade in liquid markets than on those in illiquid markets. Therefore, a liquid market reduces the cost of capital to firms and encourages real investment in the economy. Liquidity is also of interest to policy makers, regulators, and the securities exchange itself. The Johannesburg Stock Exchange (JSE) has made substantial efforts to bolster liquidity through innovation of its securities trading, clearing and settlement processes. While still a rather thinly traded market by international standards, there has been a marked improvement in the JSE's liquidity over the past two decades. The 1990s ushered in a new era of investor participation on the South African exchange, embodied by changes in local and international laws and regulations, increased information dissemination, as well as a modernisation of the market microstructure. On 7 June 1996, the final bell signalling the close of trade sounded for the last time on the open outcry trading floor. Since then, trading has been conducted electronically, but the automated trading platform has been upgraded to faster and more efficient technology no fewer than three times – in 2002, 2007 and 2012. These significant technological advancements to the market microstructure represent distinct structural breaks in the evolution of the exchange's liquidity. A direct measure of liquidity – the total annual value traded as a percentage of the market capitalisation of listed shares – ranged between 4 and 7 per cent during 1991-1994 (Johannesburg Stock Exchange Monthly Bulletin, 1991-1994). This figure was 43.2 per cent in 2015 (JSE, 2015a), a sign of the advancement in market liquidity in recent years.

The increased liquidity brought on by the continuous upgrades of the electronic trading systems stimulates high-frequency and algorithmic trading (AT) activity, which facilitates arbitrage and decreases the autocorrelation of stock returns, as concluded in Chaboud, Chiquoine, Hjalmarsson and Vega (2014) in their analysis of algorithmic trading in the foreign exchange market. High-frequency and algorithmic trading uses computer programmes to place trades based on a defined set of instructions, at speeds and frequencies impossible for human traders.

1.3 LIQUID AND EFFICIENT MARKETS

The myriad of studies, both theoretical and empirical, on both market liquidity and market efficiency (in Fama's (1970) sense and Shiller's (1981; 2003) sense) evidences the significance of these topics to finance academics and practitioners. But what is most interesting and relevant to investors and listed firms alike, is the interaction between the two. Specifically, how does the structure of a market – including the ease of transaction – influence price formation and behaviour? Intuition tells us that if the market microstructure enables easier, faster, and less costly trading activity, then astute investors should more readily exploit deviations from efficiency. When return predictability materialises, agents recognising the pattern will eradicate it through their trading. When new information arrives, traders can act on it without fear of undue sacrifice on the price, and in the process they bring prices closer toward equilibrium or full-information values. Accordingly, market liquidity should have a close relationship with market efficiency, since it affects the price discovery function, as well as uncertainties relating to how well market prices reveal all available information or the temporary divergence of market prices from equilibrium values (Muranaga, 1999; Muranaga & Shimizu, 1999).

Understanding the relationship between market structure, liquidity and price behaviour is important for theoretical and practical reasons (Madhavan, 1992). The efficiency of price formation under alternate trading designs sheds light on the factors affecting the aggregation of information in prices. Additionally, Madhavan (1992) points out that the securities industry is experiencing rapid structural shifts generated by intermarket competition and innovations in communications technology. Therefore an understanding of the relationship between market structure and price formation is needed to evaluate the impact of these changes and to guide public policy. If one can clarify the mechanism which most affects the price discovery process, it will provide a good reference in considering measures designed to improve market efficiency.

It seems reasonable to assume that trade ought to be easier in a more active exchange, and the market should thus be more liquid. Indeed, Demsetz's (1968) seminal work showed that more frequently traded stocks have smaller bid-ask spreads. Existing research papers on the relation between stock price movements and trading activity (Hiemstra & Jones, 1994; Lo & Wang, 2000) are myopic to the extent that they rely on volume as a measure of trading activity – this overlooks the implications of imbalances for stock return behaviour (Chordia & Subrahmanyam, 2004). Order imbalances are more powerful than conventional measures of trading activity in explaining stock returns because market makers react to high absolute order imbalances by adjusting their inventory, and order imbalances signal excessive investor interest in a share, which, if autocorrelated, could induce a relationship between order imbalances and future returns. Chordia, Roll and Subrahmanyam (2008) delve into the link between market liquidity and market efficiency by conducting analyses using return, order flow, and liquidity data for New York Stock Exchange (NYSE) stocks that traded every day over the period 1993 to 2002, using five-minute intraday intervals to analyse order flow and returns. The structural breaks that define exogenous changes in liquidity regimes are denoted by discrete reductions in the minimum tick size, which correspond to decreases in bid-ask spreads. The rationale is that short-horizon return predictability from the lagged order imbalance (a measure of trading activity) is an inverse indicator of market efficiency. Returns are not predictable over a daily horizon, but market inefficiencies can arise during very short, intraday horizons if investors need time to process new information or if they face constraints that limit their transactions. Chordia *et al*. (2008) find that short-horizon return predictability declines significantly during more liquid regimes, and variance ratio tests using intraday and daily midquote returns point toward greater conformity to random walk benchmarks during more liquid regimes. The authors interpret their empirical results as indicative of an intimate link between daily liquidity and intraday market efficiency; market efficiency (in Fama's (1970) sense) improved during times of enhanced market liquidity.

Financial market inefficiency does not rest solely on the presence of price predictability or the lack of convergence to a random walk benchmark. Even if prices cannot be predicted from past public information, they can reflect varying levels of private information. In addition to reducing stock return predictability, exogenous increases in liquidity may result in a more effective incorporation of new information into prices, if the increased liquidity is accompanied by lower trading costs, such as bid-ask spreads or measures of price impact. Such a cost reduction is more conducive to trading on private information about fundamental values, and enhances informational efficiency (Admati & Pfleiderer, 1988). Besides the costs of transacting, the extent to which stock prices reflect all information hinges on the cost of producing information: the smaller these costs, the more efficient is the market (Chordia, Roll & Subrahmanyam, 2005). Chordia *et al*. (2008) confirm this hypothesis using two statistics associated with information processing. They find that open-to-close/close-to-open return variance ratios increased and first-order daily return autocorrelations decreased (especially for small firms) as liquidity improved. These two results together signify increased trading on private information (French & Roll, 1986). The evidence of Chordia *et al*. (2008) suggests that liquidity increases the efficiency of accommodating order flows, encourages arbitrage activity, and engenders an incorporation of private information into prices, which in turn improves the market's informational efficiency.

The primary aim of this study is to understand whether changes in market liquidity levels of the JSE are related to variations in its degree of efficiency. Specifically, liquidity (measured by an aggregate market turnover metric) can enhance efficiency via two channels. First, liquidity may facilitate arbitrage activity by allowing faster and less costly trading. High-frequency and algorithmic trading are conducted on an electronic platform. The faster, cheaper and more efficient the trading process, the more high-frequency and algorithmic activity will infuse daily trading; this increase in arbitrage activity may diminish return predictability. This first 'efficiency channel' is tested using measures of daily return predictability and conformity to a random walk benchmark. Second, liquidity encourages trading on private information as it allows smart investors to trade large quantities quickly, at low cost, with little price impact. This enhances informational efficiency by bringing prices closer to fundamental or full-information values. This second 'efficiency channel' is tested using a metric of price volatility when the market is open versus when it is closed. The improvement in market efficiency brought about by an increase in market liquidity results in efficient fund and risk allocation (Muranaga & Shimizu, 1999). A secondary aim of the study is to find alignment between the two concepts of market efficiency: return predictability and informational efficiency.

No market is ever perfectly efficient, as no market is ever perfectly competitive or frictionless. The empirical question has always been to what extent a given phenomenon approaches this unattainable ideal (Fama, 1970).

2 LITERATURE REVIEW

The following discussion of the relevant literature is broken into two broad sub-sections: first, an outline of the theory and evidence around market efficiency, and second, an overview of the literature on the linkages between liquidity and measures of market efficiency.

2.1 EFFICIENT CAPITAL MARKETS

2.1.1 A BRIEF HISTORY

Fama's (1970) formalisation of the theory of efficient capital markets imbued the model with implications that could be tested in an empirical context. In particular, stock returns are a 'fair game' and in equilibrium, prices fully reflect the relevant information set so that investors cannot expect to achieve returns in excess of equilibrium expected returns, where the equilibrium is defined in terms of an asset pricing model. The random walk nature of stock price changes can be thought of as an extension of the 'fair game' efficient markets model, which 'arises within the context of [the fair game] model when the environment is (fortuitously) such that the evolution of investor tastes and the process generating new information combine to produce equilibria in which return distributions repeat themselves through time' (Fama, 1970, p. 387).

The efficiency of markets was recognised as early as Bachelier (1900), and the difficulty of earning returns that beat the market was noted by Cowles (1933; 1944). Later, Kendall (1953), in his analysis of serial correlations in stock and commodity price series, would make his famed 'Demon of Chance' analogy in describing the 'wandering series' of random fluctuations in price changes that he observed. Other notable contributions to the empirical literature that would culminate in the random walk model include Roberts (1959), Osborne (1959) and Working (1960). Samuelson (1965) presented a proof that in a competitive and well-functioning market, price changes follow a random walk with no predictable bias.

The EMH recognises three degrees of market efficiency. Weak-form, semi-strong form, and strong-form efficiency describe states in which prices reflect all past, public, and private information, respectively. It is generally accepted that most markets are at least weak-form efficient (Fama, 1970). In a semi-strong form efficient market, asset prices adjust instantaneously to reflect public information, but varying degrees of private information can be reflected in prices in such a market (Chordia, Roll & Subrahmanyam, 2008). Strong-form efficiency dictates that the stock price reflects all relevant information, public and private. It would be impossible to use *any* information to realise an abnormal return in this situation.

The EMH has proven resilient to considerable empirical challenges, which can be attributed to the joint hypothesis problem: any test of market efficiency is effectively a test of the joint hypotheses of market efficiency and the asset-pricing model used as the benchmark (most commonly, the Capital Asset Pricing Model or CAPM). The documentation of persistent stock market anomalies is one manifestation of the conundrum posed by the intertwined EMH and asset pricing theory. Basu (1977) observed that portfolios of low price-to-earnings (P/E) stocks earned excess returns over their high-P/E counterparts, after controlling for the CAPM. Banz (1981) found that stocks with small market capitalizations earned positive abnormal returns relative to the CAPM expected returns and to large-capitalization stocks. Fama and French (1992) showed that much of the cross-sectional variation in stock returns can be captured by a model comprising the traditional CAPM market beta combined with factors for size and the ratio of book-to-market equity (B/M), which subsumed the roles of earnings-to-price (the inverse of P/E) and leverage in predicting returns. While the size effect weakened after the 1990s, the B/M phenomenon remains as strong as ever, pervading stock markets in South Africa and abroad (Auret & Sinclaire, 2006; Basiewicz & Auret, 2009; Bauman, Conover, & Miller, 1998). Despite Fama and French's (1992; 1993) success in explaining the influence of B/M in terms of rational asset pricing theory, there is evidence that its predictive power stems from investor behavioural factors (Lakonishok, Shleifer & Vishny, 1994). The latter case clearly represents a contradiction of the EMH: a strategy of buying high B/M stocks and/ or selling low B/M stocks can earn predictable, positive abnormal returns for an investor, in excess of what is implied by the risk of the strategy.

There exists an uncomfortable dichotomy between the notion of market efficiency in the sense of security price reactions to new information, and the parallel sense of how closely prices conform to fundamental, 'rational' values. Shiller (2003) describes market efficiency as an idealistic state of rational expectations in which speculative asset prices always reflect the best information pertinent to their fundamental values, and change only due to rational updating on the emergence of new information about fundamental values. The challenge to rational market efficiency has been concentrated in evidence of excess stock price volatility (Shiller, 1981) and behavioural finance theory (Shiller, 2003).

A few points are worth noting here. First, what exactly is 'fundamental value'? It is an entirely hypothetical estimation based on the entirely subjective views and assumptions of a great number of individual market participants. It is a near-impossible task to determine the true fundamental value. Who is to say if one investor's estimation is better than that of the next investor? Moreover, even if the progression of future asset returns is such that one investor seems superior in estimating fundamental value, this could be due to pure chance rather than any genuine skill. In a market with diversity of opinion and uncertainty of tomorrow, how can one know if the fundamental value is reflected in the stock price? Second, nowhere in Fama's (1970) paper is there any mention of fundamental value. It is entirely possible for the stock price to be weak-form efficient according to Fama (1970) - it cannot be predicted from past public information - but at the same time to be incorrectly valued, as there is some information about fundamental value that is not reflected in the price. The reconciliation of Fama (1970) and Shiller (1981; 2003) into a central concept of efficiency seems elusive. However, a first step can be taken in recognising that strong-form efficiency (Fama, 1970) can be considered a state in which market prices reflect fundamental value, provided that investors process all information rationally. Strong-form efficiency corresponds to a fully revealing rational expectations equilibrium (Madhavan, 1992). A strong-form efficient market bars abnormal profits from trading on any information about asset prices – by definition, then, the price should reflect economic fundamentals.

2.1.2 NOISE TRADERS, INFORMATION TRADERS, AND EFFICIENCY

O'Hara (1997, p. 153) explains that new information becomes incorporated into securities prices due to the trading behaviour of informed and uninformed traders. Yet, price adjustment is not instantaneous – as prices are conditional expected values, the price at each point reflects all public information, but not necessarily all private information. This is because of the inhibiting effects of noise traders and limits to arbitrage on the informed traders' ability to reflect their private information in prices. Until prices adjust to the new, full-information values, informed traders earn a return on their information and prices are only semi-strong form efficient.

The antecedent piece to the microstructure literature was Working (1960), who documented that the use of time-averaged security prices could induce autocorrelation into returns series (Dimson & Mussavian, 1998). This issue of time-averaging was the first research on thin trading. One of the earliest writings on market microstructure was Jack Treynor's article on the adverse selection costs imposed by informed traders on the general investor population, written under the pseudonym of Bagehot (1971). The market-maker loses when trading with informed investors, but more than makes up for this loss by charging a 'spread' between the bid price - the price at which the dealer purchases a share - and the ask/ offer price - the price at which the dealer is willing to sell the share (Glosten & Milgrom, 1985). Thus the dealer's loss is actually borne by the uninformed investors who trade with him, and whom most likely constitute the majority of the investor population. This idea provided early understanding of how stock market efficiency is affected by the structure of the market, and the way in which investors' trading impounds information into stock prices. Kyle (1985) formalised the Bagehot (1971) idea into a price formation model in which the transactions of a single informed trader result in only a slow incorporation of his superior knowledge into stock prices, due to the noise created by the uninformed traders. Because the market maker is unable to discriminate between order flow that is produced by informed traders and by noise traders, it sets prices that are increasing in the order flow imbalance which may imply informed trading. The consequence is a positive relation between the order flow and price changes. Poterba and Summers (1988) noted that the tendency of stock prices to show long-term mean reversion can be explained by the impact of uninformed noise traders on stock prices, and is suggestive of a market inefficiency.

A fascinating insight discussed in Bernstein (1987) and theoretically derived in Campbell and Kyle (1993) is the somewhat contradictory role of noise traders in markets. On one hand, noise traders represent the other side of the transaction for information traders. Information traders are reluctant to trade with one another for fear of adverse selection. The economic function of noise traders is to make trade and therefore price formation possible. On the other hand, noise traders by definition act on imperfect information and can push company stock prices away from fundamental values. Herein lies the essentiality of the information trader's role: attracted by the mispricing created by noise traders, the information trader will exploit such mispricing to bring prices back to fundamental values. Black (1986, p. 532) summarises the paradox: 'Noise trading actually puts noise into prices… Prices will be less efficient. What's needed for a liquid market causes prices to be less efficient'. Noise makes financial markets possible, but also makes them imperfect.

The ability of informed traders to profit from the mispricing induced by noise traders is referred to as incomplete arbitrage. It is noted that this terminology is not in harmony with the conventional meaning of 'arbitrage', as taking two offsetting market positions in order to earn a riskless profit; it describes the exploitation of any mispricing, which cannot be perfectly hedged and will most likely expose the arbitrageur to some risk (McClelland, 2014). The efficiency of a securities market depends largely on the reliability of arbitrage in exploiting mispricing, thereby eliminating predictability in security returns and/ or bringing prices to fundamental values. Shleifer and Vishny's (1997) study, 'The Limits of Arbitrage', focusses on the operational obstacles to arbitrage as well as the pattern of investor sentiment that can allow stock return predictability and pricing anomalies to thrive in a market. Chordia, Roll and Subrahmanyam (2008) suggest that market illiquidity is a barrier to the extensiveness and effectiveness of arbitrage. Grossman and Stiglitz (1980) argue that perfectly competitive markets are impossible when arbitrage is costly, because if all arbitrage profits are eliminated, there is no incentive for informed traders to incur the cost of arbitrage. The model proposed in their paper envisions an 'equilibrium' in which prices only partially reflect the information of informed traders, so that there is incentive to collect costly information. However, when information is costless and equilibrium prevails, prices reflect the information of the informed traders. But because traders have almost homogenous beliefs, the market is likely to be illiquid. This conundrum beguiles one to explore how market efficiency, in the spirit of both Fama (1970) and Shiller (1981; 2003), is related to market liquidity. Serially correlated noise in security returns is a feature of deviations from a random walk, but could also convey the amount of private information about fundamentals incorporated into prices, or the informational efficiency of the market. How these alternate metrics of financial market efficiency interact with market liquidity is an interesting problem that can further the search for common ground between Fama (1970) and Shiller (1981; 2003).

2.2 THE LIQUIDITY LITERATURE

It can be argued that the powerful role of individual asset or broad capital market liquidity in investment theory did not receive due attention in early theses and empirical research. However, in recent decades, the two questions of how liquidity informs asset pricing, and how it affects efficient price formation, has piqued the interest of academics. It is important to make a distinction between these two separate, but related, lines of research.

2.2.1 LITERATURE ON LIQUIDITY AS A PRICED SOURCE OF RISK

Liquidity describes the ability to trade sufficient quantities of an asset quickly, at low cost, with minimal price impact (Liu, 2006). Intuitively, a low-liquidity stock would most likely be small, value, high bid-ask spread, low turnover or trading volume, and would suffer significant price impact when substantial trades are executed. Investors would rationally require a premium for holding these stocks. Less liquid stocks are more difficult to trade and expose the investor to considerable 'lock-in' risk, especially if market-wide liquidity happens to dry up. Consequently, we would expect the liquidity premium to be more pronounced when the market as a whole is less liquid, and cyclically during times of recession. This was posited in Pastor and Stambaugh (2003), who find there is a premium for high sensitivity to aggregate liquidity. Market-wide liquidity is therefore an important state variable for asset pricing.

One of the first papers to examine the priced nature of illiquidity risk was Amihud and Mendelson (1986). The authors provided theoretical and empirical proof of the positive relation between (relative) bid-ask spreads and market-observed average returns, and that net of transaction costs, asset returns to holders increase with the spread. In addition, there is a clientele effect that is characterised by longer-horizon investors holding stocks with higher spreads, which causes returns on higher-spread stocks to be less spread-sensitive. Importantly, Amihud and Mendelson (1986) note that they do not consider their results to be indicative of a market inefficiency, but of a rational response by investors in an efficient market when faced with trading friction and costs.

Amihud (2002) explores the relationship between expected stock return and expected stock illiquidity using the average daily ratio of absolute stock return to dollar volume as an illiquidity indicator. This measure emphasises the price impact dimension of illiquidity. It is shown that expected stock returns increase with expected illiquidity, both in the cross-section and across time. The results also indicate that ex ante stock excess return is an increasing function of expected market illiquidity, and innovations in market illiquidity lower contemporaneous stock prices.

A formal Liquidity-Augmented Capital Asset Pricing Model was developed in Liu (2006), with two factors (market and liquidity) explaining the cross-section of stock returns for a sample of NYSE/AMEX/NASDAQ stocks over the period 1960-2003. The multidimensionality of liquidity is accounted for through a single measure that captures the speed, quantity, costs and price impact of trading. The model captures a significant liquidity premium robust to the

CAPM and the Fama–French (1993) three-factor model, and subsumes the size and value effects. Liu's (2006) mimicking liquidity factor is negatively correlated with the market, confirming the conjecture that the premium required for holding low-liquidity stocks is greater during recessionary periods. The mimicking liquidity factor is significantly correlated with innovations in the market-wide liquidity measure that seems to describe aggregate market liquidity conditions.

Prior to Liu (2006), Acharya and Pedersen (2005) independently derived their own Liquidity-Augmented Capital Asset Pricing Model using the Amihud (2002) return-to-volume measure of illiquidity risk, and find that when testing the cross-sectional predictions of the model, it is able to capture the size effect but not the book-to-market effect. Acharya and Pedersen (2005) also find evidence consistent with 'flight to liquidity' when aggregate liquidity is low: less-liquid stocks tend to have high commonality in liquidity with market liquidity, high return sensitivity to market liquidity, and high liquidity sensitivity to market returns. These three channels of liquidity risk differ in their respective contributions to the effect of liquidity on asset prices. The authors emphasise the importance of stock liquidity sensitivity to the market return – this element contributes to the majority of the estimated liquidity risk premium. They also conclude that the effects of liquidity level and liquidity risk are separate.

Equilibrium asset-pricing models are by nature simplifications of reality, based on underlying assumptions such as perfect capital markets and an absence of trading frictions. Most of the extant asset-pricing literature abstracts from the features of the markets in which assets trade. The market microstructure literature, by contrast, centralises the mechanics of the trading process in affecting price formation and how information is incorporated into prices (Easley, Hvidkjaer & O'Hara, 2002). While an analysis of microstructural models of price efficiency, volatility, and the extent of private information is beyond the scope of this research (see O'Hara (1997) for a discussion and derivation of microstructure models), it is worth noting that the reliance of traditional asset-pricing models on prices being set 'efficiently' ignores the dynamic nature of efficiency. In a static-efficiency world, information is instantly reflected in the prevailing asset price, without conceptualising how information comes to be reflected in the price. If prices are continually revised to incorporate new information, then efficiency is a process, and how asset prices become efficient cannot be separated from asset returns at any point in time (Easley, Hvidkjaer & O'Hara, 2002).

Brennan and Subrahmanyam (1996) draw on market microstructure theory to show that there is a significant return premium associated with both the fixed and variable components of the cost of transacting. Monthly stock returns are significantly related to measures of illiquidity obtained from intraday transactions data, after adjusting for the Fama and French (1993) risk factors and after accounting for the effects of the stock price level. They reason that the primary cause of illiquidity in financial markets is the adverse selection costs arising from the existence of information asymmetry, and this significantly affects expected asset returns.

It is almost instinctive to think of transactions costs and liquidity in the context of the repeated trading of a single homogenous asset. But the broader market determinants of liquidity, beyond that of individual assets, may have implications for microstructure theory as well as for investors and regulators. There is covariation in liquidity and associated co-movements in some component of transactions costs through time. Liquidity, trading costs and other microstructure phenomena have common underlying determinants (Chordia, Roll & Subrahmanyam, 2000; Hasbrouck & Seppi, 2001). Huberman and Halka (2001) surmise that a systematic component of the temporal variation in liquidity may be created by the presence and effect of noise traders. Commonality in liquidity offers economic reasoning on liquidity risk in asset pricing (Liu, 2006), as varying sensitivities to covariation in trading costs leaves certain assets more vulnerable to broad liquidity shocks. This would represent a source of non-diversifiable priced risk. Additionally, as advanced in Chordia *et al*. (2000, p. 3), 'Recognising the existence of commonality is a key to uncovering some suggestive evidence that inventory risks and asymmetric information both affect intertemporal changes in [individual stock] liquidity'.

2.2.2 LIQUIDITY, PRICE DISCOVERY AND PRICE FORMATION

A fair market price is one that mirrors the demand propensities of all traders, unembroidered by incomplete information, unperturbed by shocks to the order flow, unobscured by periods of market thinness, and unaffected by the market trading system (Schreiber & Schwartz, 1986, p. 43). John Maynard Keynes (1936, p. 103), in his well-known beauty contest analogy of securities markets, concludes that securities trading is an art of 'anticipating what average opinion expects the average opinion to be'. Market prices are driven by the average of heterogeneous expectations and the trading propensities of the investor population. The effectiveness of security prices in reflecting the average opinion is the essence of price discovery in securities markets. Price changes are influenced by market mechanics - factors such as the bid-ask spread, thin trading, and market maker intervention – as well as the information processing or price discovery of market participants (Schreiber & Schwartz, 1986). Price discovery and thus price adjustment is not immediate, and noise obfuscates the informational content of prices – leaving short-horizon asset returns to be serially dependent and short-horizon return variance to be higher relative to longer horizons.

2.2.2.1 LIQUIDITY AND RETURN PREDICTABILITY

Market microstructure theory qualifies the volume dimension of stock market liquidity in terms of depth, breadth and resiliency (Bernstein, 1987; Kyle, 1985). The amalgamation of these in a market is not an end in itself; but prompts information traders to trade on the inefficiencies created by noise traders. It is the noise trader who provides the depth, breadth and resiliency that make it possible for trade to occur. Depth and breadth describe the ease with which a large number of trades can be executed within a short period of time. Breadth refers to the existence of orders in ample volume, and depth typifies the existence of orders on both sides of the book close to the current trading prices of stocks (Hasbrouck & Schwartz, 1988). A resilient market is one with a large 'countervailing order flow whenever transaction prices change because of temporary order imbalances' (Garbade, 1982, p. 428).

Chordia, Roll and Subrahmanyam (2002) documented a significant predictability of daily market-wide order imbalances (defined as aggregate daily purchase orders less sell orders). A high aggregate buy-side imbalance on one day is likely to be followed by several more days of buy-side imbalance, and likewise for a high initial sell-side imbalance. This pattern of extended buying or selling can be interpreted as either due to herding behaviour or splitting large orders across days, or both. In two extended papers, Chordia and Subrahmanyam (2004) and Chordia, Roll and Subrahmanyam (2005) confirm this positive dependency in daily order imbalances and further note that these imbalances predict future short-horizon stock returns. The 2005 paper also shows a negative serial dependence in returns over ten-minute intervals, conditional on the current order imbalance. Because only the market maker has absolute knowledge of order imbalances, this suggests that the market maker controls its inventory risk by adjusting quotes away from fundamentals (Amihud & Mendelson, 1980; Amihud & Mendelson, 1982; Ho & Stoll, 1981). Countervailing traders quickly recognise the price pressures induced by order imbalances and step in to remove the patterns in no more than thirty minutes. The Chordia and Subrahmanyam (2004) empirical study supplements their intertemporal framework of how prices react to imbalances when risk-averse market makers have to accommodate positively autocorrelated trader demands.

Stock return predictability is not a necessary implication of an illiquid market (Kyle, 1985). Chordia *et al*. (2008) provide three competing theoretical arguments for how return predictability from order flows can emerge. In the first scenario, market makers are constrained in their risk-bearing capacity and/ or inventory financing. Positively autocorrelated order imbalances create price pressures that can lead to transient patterns, such as short-horizon predictability of returns from lagged order flows. The arbitrage trader, if able to take advantage of the pattern, will do so until it is eliminated. However, illiquidity may limit the pervasion and effectiveness of arbitrage trading. The second mechanism is a behavioural one inspired by the Barberis, Shleifer and Vishny (1998) behavioural model: if market makers react sub-optimally to the pattern of order flow, a mispricing would arise. Outside market participants would attempt to profit from this by trading on information about order flow. This imposes an adverse selection cost on the market maker; the market may be less liquid as a result, even if prices are theoretically more efficient because more information is impounded into them. In this case, increased efficiency is associated with less liquidity. Lastly, there may be no relation between illiquidity and return predictability from order flows, if market makers rationally absorb imbalances and rapidly update quotes without outsider assistance. Based on their analysis, Chordia *et al*. (2008) lean toward the first hypothesis.

Chung and Hrazdil (2010) conduct the Chordia *et al*. (2008) analyses on a more comprehensive sample of NYSE shares to examine potential confounding effects of trading frequency and firm size on the liquidity-efficiency relation. Unlike Chordia *et al*. (2008), whose study was restricted to only 193 large-capitalisation firms that traded every day during 1993-2002, Chung and Hrazdil (2010) include all firms listed on the NYSE between 1993 and 2004. Although their results show a general improvement in efficiency for portfolios formed on trading frequency, volume, and market capitalisation, there is significant heterogeneity in short-horizon return predictability from past order flows across portfolios. They advise that regression analyses in cross-sectional research studies control for trading frequency, volume and market capitalisation when performing market efficiency estimations. The authors further extend the liquidity and information effects analysed in Chordia *et al*. (2008) by asking whether and to what degree these effects drive the cross-sectional variations in short-horizon return predictability. They do this by adopting a two-stage regression approach: in the first stage, they replicate the Chordia *et al*. (2008) methodology. In the second stage, they move away from the portfolio approach and examine return predictability on a firm-level basis. They relate market efficiency to the effective bid-ask spread (twice the absolute difference between the transaction price and the midpoint between prevailing quoted prices), to further demonstrate how liquidity affects return predictability. Then, they identify phases of high adverse selection in the market and show how the liquidity and market efficiency dynamic changes during these informational periods. Overall, they support the Chordia *et al*. (2008) hypothesis that increased liquidity enhances market efficiency as it facilitates arbitrage activity, which helps the market maker absorb investor demand. They also confirm that past order flows contain public information about future returns, and that the convergence to market efficiency, or the time taken for prices to fully reflect new information, is not instantaneous (Chordia *et al*., 2005). There is an increase in return predictability when new information arrives, and the effect liquidity has on market efficiency is more pronounced during such informational periods. They conclude that increased liquidity encourages the price discovery process and a more efficient incorporation of information into prices by reducing the effect of asymmetric information on short-horizon market efficiency.

2.2.2.2 LIQUIDITY AND VOLATILITY

In addition to return predictability, financial market efficiency can be assessed using the variance or volatility of short-horizon returns relative to long-horizon volatility. Chordia *et al*. (2008) reasoned that because the long-horizon return variance should be q times the variance of short-horizon returns, where q is the number of short-horizon periods within the longer horizon, the scaled ratio of these values should converge to unity in large samples. A variance ratio significantly above unity implies that the trading process induces noise in stock returns.

What is particularly interesting about testing for noise in security price returns is the continuum of interpretations it inspires. The lines between Fama's (1970) market efficiency and Shiller's (1981; 2003) market efficiency become somewhat blurred when comparing interpretations. Noise could indicate lack of conformity to a random walk price process. Deviations from random walks can materialise as return serial correlation is introduced through the inventory control activity of the market maker (Grossman & Miller, 1988; Madhavan, Richardson & Roomans, 1997), or because uninformed trade is not independent and identically distributed (Easley, Kiefer & O'Hara, 1997). In Black's (1986, p.529) model of financial markets, noise is contrasted with information: '[Noise] is what makes our observations imperfect. It keeps us from knowing the expected return on a stock or portfolio'. Noise causes the short-term volatility of price to be greater than the short-term volatility of value. The variances will converge over longer intervals. Clearly, the influence of noise signifies a violation of both Fama's (1970) and Shiller's (1981; 2003) versions of efficiency. The crucial difference is what each scenario implies for financial market liquidity. Liquidity should be associated with enhanced efficiency if it eases the elimination of return predictability and a restoration of random walk benchmarks (Chordia *et al*., 2008). Conversely, in Black's (1986) model, noise trading is associated with increased liquidity as noise traders represent the other side of the transaction for information traders, but prices are less efficient as the value of information reflected in them is obscured by noise. Thus, an analysis of the noise in stock returns across liquidity states can provide insight into how noise interacts with market liquidity.

Black (1986) goes on further that noise will only permeate prices when noise traders trade, and information traders trade more with noise traders than they do with one another. The result is that prices will not move as much when the market is closed as when it is open. This increase in stock return volatility during market trading hours is precisely what French and Roll (1986) found in their study of information processing in financial markets. Although around 4-12% of the daily variance is due to pricing errors, they ascribe high trading-time variances principally to private information which affects prices when informed traders trade. Thus, the behaviour of returns during trading hours is linked to informational efficiency in the spirit of Kyle (1985). Chordia *et al*. (2008) use this measure of trading-time versus non-trading time variances across liquidity regimes to discern whether higher liquidity aids privately informed trading and thus an increased incorporation of information into prices when the market is open. They show that this ratio increases over time, and consider first-order daily return autocorrelations to discriminate between the mispricing and the private information hypotheses. French and Roll (1986) conjecture that significant autocorrelation suggests mispricing either due to investors' reaction biases or microstructural frictions. Although Chordia *et al*. (2008) provide evidence of positive autocorrelations, there is no evidence that autocorrelations increased along with trading-time volatility. Thus the observed increase in trading-time variance is not due to increased mispricing, but the more effective incorporation of private information into prices when informed traders find it more profitable to trade as transaction costs are lower.

Chung and Hrazdil (2010) take a different approach in evaluating how liquidity assists the incorporation of information into prices. They identify 'informational periods' as those when the adverse selection component of the bid-ask spread is relatively higher (Glosten & Milgrom, 1985), and find that during such periods, the positive effect of liquidity on market efficiency is significantly more pronounced. Therefore the degree to which prices incorporate information depends on market liquidity.

Fleming and Remolona (1999) study price formation and liquidity in the U.S. Treasury market. They identify a two-stage adjustment process for prices, trading volume and bid-ask spreads upon the arrival of public information. The first stage sees a sharp and almost instantaneous price change with a reduction in trading volume when major macroeconomic news is released. The inventory control concerns of the market maker induce a widening of spreads and a marked disruption of liquidity. In a prolonged second stage, trading volume increases dramatically, price volatility persists, and spreads remain wide due to the role of differential private information. The reconciliation of divergent views is a protracted process: He and Wang's (1995) model of investors with differential information results in persistence in price volatility and trading volume in a slow convergence to a consensus price. The noise in prices obscures the revelation of traders' private information, facilitating persistence in volume and volatility.

2.3 THE SOUTH AFRICAN CASE

2.3.1 THE JOHANNESBURG STOCK EXCHANGE: EVOLUTION OF A TRADING SYSTEM

Market frictions are a reality of most, if not all, trading systems. The efficiency of market outcomes such as price and trade determination then hinges in some manner on the design features of the market (Schreiber & Schwartz, 1986). Trade in financial assets has increasingly become a game of speed. Stoll's (2006) view is that electronic trading enhances market efficiency by decreasing the cost of providing liquidity, and ensuring faster trading and more accurate price signals.

A stream of empirical literature has emerged, aimed at identifying exogenous changes in market structure that encourage high-frequency activity, and the consequences thereof (Hendershott, Jones & Menkveld, 2011; Menkveld, 2013; Riordan & Storkenmaier, 2012). Conrad, Wahal and Xiang (2015) focus on the influence of high-frequency quoting on market efficiency and price formation in the case of an exogenous technological upgrade to the trading system of the Tokyo Stock Exchange. They find that prices more closely resembled a random walk and that trading costs declined sharply when the new system was implemented. Boehmer, Fong and Wu (2012), using an international sample spanning the period 2001-2009, conclude that algorithmic trading intensity enhances liquidity and informational efficiency, while also increasing volatility.

Formed in 1887, the Johannesburg Stock Exchange (JSE) is one of the largest exchanges in the world by market capitalisation (World Federation of Exchanges, 2013), and is certainly the largest exchange in Africa. South Africa's capital markets are mature even by developed market standards, serving economies in the local sphere and the broader African continent. Size and scale do not however equate to market liquidity. The speed, ease and cost effectiveness of entering and exiting a position would be a primary element in determining the attractiveness of a marketplace to both domestic and international investors. Globalization of real and financial markets has amassed a legion of international traders in search of opportunities in foreign markets. International investors would be especially attracted to a liquid market through the assurance of easy access and speedy exit. Furthermore, the ability to profit from observed inefficiencies for any significantly-sized portfolio would be hampered by illiquidity, resulting in persistent market anomalies (Bailey & Gilbert, 2007). Institutional investors would find it particularly difficult to invest large sums into a market when its available liquidity constrains the number of shares that could be bought or sold at certain prices.

A 1994 report by a JSE-appointed research sub-committee on the future structure of the JSE concluded that liquidity on the JSE, as defined by annual turnover as a percentage of market capitalisation, was unsatisfactorily low (Katz, 1994). Measures to improve liquidity include increasing the volume of trade; improved information disclosure; and changes to the system of trade (De Villiers, 1996).

Today, the JSE looks very different. This change has transpired through structural forces such as a higher volume of trade, due to greater participation from local and international investors and enhanced information dissemination, and improvements to the system of trade.

The increase in volume of trade can be ascribed to changes in tax rules and methods to encourage firm disclosure of information. The 1997 launch of the Stock Exchange News Service (SENS) represented an important breakthrough in information dissemination and transparency for the South African market, heightening investor confidence. The service distributes news of corporate announcements and price-sensitive information in real time.

The JSE continues to make improvements to the efficiency and speed of the trading, clearing and settlement processes through changes to the market microstructure. The year 1996 marked the end of 108 years of open-outcry floor trading. All trade was moved to an automated, order-driven, central trading platform, the Johannesburg Equities Trading (JET) system. Dual trading and negotiated brokerage commissions were also introduced (JSE, 2015b). A second milestone in the technological revolution was the introduction in 1997 of Shares Transactions Totally Electronic (Strate), the electronic clearing and settlement concept. The JSE experienced a boost in trading volumes upon adoption of the JSE SETS trading platform in 2002, and again when the JSE TradElect system, licensed from the London Stock Exchange, was implemented in 2007. In July 2012, the JSE launched the equity trading platform Millennium Exchange, enabling the execution of transactions at speeds almost 400 times faster than the previous trading solution. The adoption was expected to increase trading volumes as it facilitates a proliferation of high-frequency and algorithmic trading activity, and thus higher market liquidity. Indeed, this effect was inferred in Hattingh (2014). Increases in trading speeds led to a rise in levels of trading and depth of the market (JSE, 2011).

Concomitant to the 2012 revamp was the move of the trading engine from London to the JSE building in Johannesburg. The relocation eliminated certain operational problems related to international connectivity links that often resulted in a halt in trading (JSE, 2011). A strong statistical relationship between algorithmic trading and a change in JSE market structure was found in Zito (2014), with mixed evidence of a positive effect on liquidity with a corresponding increase in volatility and decrease in the average trade size. The launch of the JSE’s colocation facilities on 12 May 2014 (JSE, 2014) further advanced the speed of market access, boosting liquidity and transparency (Jain, 2005; Zito, 2014). The colocation centre allows clients to place their trading equipment in closer proximity to the trading systems of the JSE markets (JSE, 2013), providing faster access to the market and greater ability to take advantage of market movements. Colocation services clearly improve trading speeds and updates to market data, which enhance response to market movements and deployment of new trading strategies (JSE, 2014).

Improved efficiency, service and stability has solidified the status of the South African market as a world-class exchange, and a prime trading environment attracting the interest of domestic and international market players alike.

2.3.2 THE BEHAVIOUR OF JSE STOCK RETURN DATA

First-order return autocorrelations are, in general, very close to zero for actively traded stocks in developed markets. The Chordia *et al*. (2005) study exhibited that, despite persistence in the order imbalance, the S&P500 index is virtually a random walk over daily horizons. As the present research is an adaptation of the Chordia *et al*. (2005; 2008) methodologies to the smaller South African market, the local market's idiosyncrasies must be known and understood (Page, Britten & Auret, 2016). The JSE is an innately different market to the U.S. exchanges, and the South African literature is far from settled on the weak-form efficiency of the JSE.

Gilbertson and Roux (1977) presented a case for the efficiency of the JSE by remarking that, despite evidence of serial dependence in share returns, these are too small to be exploited. However, Strebel (1977) argued that the EMH is true only for the highest-volume shares listed on the JSE. Thompson and Ward (1995) reviewed the early tests of the i.i.d. random walk hypothesis on the JSE. The overall evidence was mixed, due to methodological differences in empirical tests of the efficiency of the JSE. Smith, Jefferis and Ryoo (2002) found that the JSE followed an i.i.d. random walk. Larger-capitalisation, liquid stocks are more likely to follow random walks than small, illiquid stocks (Jefferis & Smith, 2004). Smith (2008) conducted rigorous tests of the i.i.d. random walk and martingale hypotheses with weekly and monthly data for 11 African stock market price indices using joint variance ratio tests. For both the monthly and weekly return series, the author finds that the JSE All Share Index does not follow an i.i.d. random walk. However, returns are a martingale difference sequence – they are not predictable, but may contain dependence in higher moments, for example, conditional heteroscedasticity. Additionally, Smith (2008) concludes that the differing results for the various African exchanges indicate that market liquidity is an influencing factor on whether the market index follows a martingale difference sequence.

Most studies focus on linear serial dependence when testing stock return predictability. Higher-order serial dependence indicates nonlinear behaviour of share returns. Research such as that of McMillan (2004) suggests the existence of higher-order processes in the return-generating process, and due to the interaction between noise and arbitrage traders, a different treatment for large and small share returns is necessary. The results of Mangani (2007) showed significant nonlinear dependence in the returns of a sample of 42 JSE stocks, implying nonlinear predictability in the returns. Using daily data on the JSE All Share Index over 1995-2010, Babikir, Gupta, Mwabutwa and Owusu-Sekyere (2012) find no evidence of autocorrelation of daily stock returns based on closing prices. However, they do find strong serial correlations in the squared stock returns. Kruger, Toerien and MacDonald (2012) found nonlinear serial dependence in daily share price data for the JSE's All-Share Index constituents, using a battery of tests for nonlinear behaviour. Nonlinear behaviour in share returns could have a multitude of causes, which are not mutually exclusive. Examples include: challenges posed to arbitrage such as thin trading, transaction costs, and regulatory constraints; nonlinear feedback mechanisms in price movements; and irrational investor behaviour (Antoniou, Ergul & Holmes, 1997). Although significant linear and nonlinear serial dependencies were found for all shares examined in Kruger *et al*. (2012), these incidences are sporadic and transient in nature, rendering them difficult to predict and exploit over time. Thus the authors conclude that the JSE is efficient for most of the sample period investigated, interspersed with only brief periods of inefficiency characterised by serial return dependence. A similar conclusion on the weak-form efficiency of 10 Asian emerging stock markets was reached by Lim, Brooks and Hinich (2008).

Unterhorst (2014) presented empirical evidence of asymmetric reverting behaviour in the conditional mean and conditional variance of stock returns on the JSE. The effect is most acute over daily and weekly intervals. Conditional mean asymmetry describes the nonlinear reverting patterns of returns: negative returns revert faster and with greater magnitude to positive returns than positive returns revert to negative returns; causing persistence of positive returns through time (Nam, 2003). Unterhorst's (2014) results show signs of this positive-return persistence in the daily return series across market capitalisation and industry, supporting the profitability of short-run contrarian trading strategies. The finding of positive-return persistence is aligned with Chordia *et al.* (2002), who express the idea that price pressure is not a phenomenon limited to individual stocks, but also impacts returns at the aggregate market level.

Cubbins, Eidne, Firer and Gilbert (2006) detected the presence of mean reversion of share returns on the JSE. This finding prompted Bailey and Gilbert (2007) to suggest that the market is not entirely efficient, and that the persistence of the anomaly is caused by illiquidity, which hampers the ability to profit from observed inefficiencies. Due to the exacerbation of the price impact effect for larger portfolios, institutional investors' actions impact the prices at which they can actually trade in the market. The authors went on to test for the effects of liquidity on mean reversion by modifying the Cubbins *et al*. (2006) methodology to include a liquidity cap measure as a liquidity constraint from the perspective of a fund manager. Their results indicate that liquidity has an asymmetrical effect on the abnormal returns achievable through mean reversion of share returns for low-P/E versus high-P/E shares.

3 METHODOLOGY (RESEARCH DESIGN AND METHODS)

3.1 TIME-SERIES TESTS OF ORDER IMBALANCES AND RETURNS

Chordia, Roll and Subrahmanyam (2005) provide evidence of short-horizon return predictability from lagged order flow data. This relation is confirmed in Chordia, Roll and Subrahmanyam (2008), which also documents that the phenomenon dissipates during more liquid states of the market. The authors conjecture that liquidity facilitates arbitrage trading due to a reduction in the effective costs of trading.

As a first step, the Chordia, Roll and Subrahmanyam (2008) study demarcated its investigation of the liquidity-efficiency relation in the context of intraday trading. This implicitly assumes that the market studied was approximately efficient over a daily horizon, but that inefficiencies may arise during intraday trading. Returns and order flows were measured over an intraday interval of five minutes in the 2008 paper, a choice made to strike a balance between potential nontrading issues and the preservation of the integrity of the research. The authors' reason that since the predictability of returns from lagged order imbalances is not likely to survive for very long, using longer intervals may result in important patterns and short-lived market inefficiencies going undetected.

The first set of testing in this study involved an investigation of the relation between liquidity and the efficiency-creating process by focussing on return predictability in daily data. The Johannesburg Stock Exchange, at the time of writing, did not record high-frequency transactions data in a readily-accessible database such as the NYSE's Trade and Automated Quotations (TAQ) database. This means that, although the JSE was able to provide trading prices at fifteen-minute frequencies, it was not feasible to extract the associated bid and offer quotes at the same frequencies. Best bid or offer (BBO) quote data, as used in Chordia, Roll and Subrahmanyam (2001), were only available at a daily interval. As bid and offer quote data are essential to the calculation of order imbalances, the research methodology settled for the highest-frequency interval possible. Note that the terms 'offer quote' and 'ask quote' will be used interchangeably in this study, as both refer to the price at which a market maker is willing to sell a security.

Chordia and Subrahmanyam (2004) documented a positive autocorrelation in daily order imbalances, as well as a positive predictive relationship running from lagged (by one day) imbalances to current day returns. They interpret their findings as supportive of the notion that inventory effects last for time intervals longer than a trading day. Additionally, the abundant evidence for nonlinear serial price dependencies in the South African market (Babikir *et al.*, 2012; Kruger *et al.*, 2012; Mangani, 2007; McMillan, 2004; Unterhorst, 2014) provides assurance that transient incidences of market inefficiency may well still be detected at a daily horizon. Moreover, correspondence with Richard Roll, a co-author of the Chordia *et al.* (2008) paper, indicates that longer intervals may be acceptable for a developing market that is not very liquid or active. Future research should extend the methodology explored in this study as the JSE's technological capabilities continue to advance, not only in terms of microstructural developments, but also improvements in record-keeping and data-collection processes.

Clearly, the concept of an order imbalance over a time horizon has meaning only in an intermediated-market context, wherein market makers accommodate the demand and supply needs of outside investors. In any other paradigm, order imbalances would be deemed irrelevant by the classic notion of "for every buyer, there's a seller" (Chordia & Subrahmanyam, 2004).

When trading is infrequent, it becomes difficult to evaluate share return behaviour; in particular, the measurement of serial dependence at short horizons. Chordia *et al.* (2008) alleviated potential problems due to thin trading by excluding small stocks from their analysis. The share sample in this study was selected from the Top 40 constituents listed on the JSE, due to their large market capitalisations and the high likelihood that they traded every day over the time period studied. Of the current Top 40, 28 shares have been present in the index at least since the 1996 move to electronic trading, and these form the final share sample analysed in this study. The sample period studied is January 2012 – June 2016 as it covers a time of important exogenous change in the market microstructure of the exchange. Specifically, the year 2012 marked the implementation of the Millennium Exchange trading platform, an electronic trading system much faster and more efficient than any platform before it. The advancement in market microstructure represents a structural break to discern the relation between market liquidity and efficiency. Zito (2014) found a strong positive statistical relationship between the introduction of the Millennium Exchange platform in 2012 and the proliferation of algorithmic trading (AT) in the market. AT activity grew by 24% when comparing the first five week period to the last five week period studied after the implementation of the new trading platform. The increase in AT activity owing to a change in the market microstructure is in line with international theory (Hendershott *et al.*, 2011). Due to data availability constraints, the time period spanning the previous trading platform upgrades could not be analysed in this study. Future research should incorporate these important periods as the data become available.

The order imbalance for a stock over a time interval is calculated as the Rands paid by buyer-initiators less the Rands received by seller-initiators divided by the total Rand value of trading (*OIBR*):

$$OIBR_t = \frac{(Rands\ traded\ by\ buyer-initiators\ at\ t)-(Rands\ traded\ by\ seller-initiators\ at\ t)}{Total\ Rands\ traded\ at\ t} \quad (1)$$

Chordia *et al.* (2008) conduct their return predictability regressions using two alternate measures of order imbalance: *OIB$* (analogous to *OIBR* in this study), as well as *OIB#*, the number of buyer- less the number of seller-initiated trades divided by the total number of trades. *OIB#* weighs all orders equally, irrespective of size. Large orders will be weighted more heavily when using *OIBR* – providing the economic magnitude of the order imbalance. As the results of Chordia *et al.* (2008) are directionally consistent using either measure of order imbalance, this study uses *OIBR* only for brevity.

The computation process begins with the transactions and bid-offer quote data. After filtering the trade and quote data for out-of-sequence trades, each transaction was matched to a bid-ask quote. This entails setting the matching quote to be the first quote prior to the trade. Chordia *et al.* (2008) set the matching quote to be the first quote at least five seconds before the trade. However, due to a general decrease in reporting errors after 1998, the matching quote is simply the first quote prior to the trade.

Following Chordia *et al*. (2008), the Lee and Ready (1991) algorithm was applied to the matched trade-quote data to obtain an estimate of whether a particular trade was buyer- or seller-initiated. The logic behind the Lee-Ready classification is quite intuitive: it assigns a trade as buyer- (seller-) initiated if it is closer to the offer (bid) of the prevailing quote. If the trade price is exactly at the midpoint of the quoted spread, the trade is classified as buyer- (seller-) initiated if the last price change prior to the trade is positive (negative). It was then straightforward to calculate the daily order imbalance for a stock. Order imbalances were computed over all trades for each trading day examined.

Daily returns can be obtained through several methods. Returns computation using transaction prices is commonly accepted practice in finance, but such returns are affected by bid-ask bounce (Chordia *et al.,* 2008). Following Chordia *et al.* (2008), share returns were computed using the midpoints of the bid and offer quotes prevailing at the end of each trading day:

$$Return_{it} = \ln\left(\frac{Midpoint\ of\ bid\ and\ offer\ quotes\ for\ share\ i\ at\ time\ t}{Midpoint\ of\ bid\ and\ offer\ quotes\ for\ share\ i\ at\ time\ t-1}\right) \quad (2)$$

3.2 LIQUIDITY DATA

Chordia *et al.* (2008) measure market-wide illiquidity by calculating the mean bid-offer spread for each individual firm over each trading day. The use of the bid-offer spread as a measure of aggregate illiquidity is appropriate in the context of that paper, given that the structural breaks identified (reductions in the minimum tick size) would affect bid-offer spreads, or the transaction costs related to trading. However, the same reasoning cannot be applied in the context of this study, as it is not immediately obvious whether technological trading platform upgrades would affect individual firm bid-offer spreads. The likely liquidity outcome of faster, more efficient channels of trading would be most palpable when measuring turnover, or the trading quantity dimension of liquidity. Daily share turnover is defined as daily trading volume divided by number of issued shares outstanding:

$$Turnover_{it} = \frac{Trading\ volume\ of\ shares\ for\ firm\ i\ at\ time\ t}{Number\ of\ shares\ outstanding\ for\ firm\ i\ at\ time\ t} \quad (3)$$

The measure of market-wide liquidity in this study uses firm trading turnover over each trading day in the sample period. The aggregate liquidity indicator, Liq_t, is derived by value-weighting and averaging daily turnover across stocks, with market capitalisations at the end of the previous year used to calculate weights:

$$Liq_t = \sum \frac{(Turnover\ for\ firm\ i\ at\ time\ t) * (Market\ capitalisation\ of\ firm\ i)}{Total\ market\ capitalisation\ of\ share\ sample} \quad (4)$$

Structural breaks in the market's trading processes logically should be linked to enhanced liquidity, which would be confirmed by time-series variations in the aggregate liquidity measure. Chordia *et al*. (2008) observed that when bid-ask spreads are narrower, short-horizon return predictability is diminished. Although the bid-ask spread is a widely used liquidity proxy (Amihud & Mendelson, 1986; Chordia, Roll & Subrahmanyam, 2008; Easley, Kiefer, O'Hara & Paperman, 1996), it is a one-dimensional measure that only captures the facet of liquidity characterised by direct trading cost (Liu, 2006). Yet, the Amihud (2002) and Pastor and Stambaugh (2003) measures, that capture price reaction to trading volume, are not readily computable as daily measures (Chordia *et al.*, 2008). These issues could be alleviated through the use of a liquidity indicator analogous to Liu's (2006) liquidity measure, *LMx*, for the aggregate market. *LMx* is constructed as the standardised turnover-adjusted number of zero daily trading volumes over the prior *x* months.

The advantage of using *LMx* is its ability to capture the multidimensional nature of liquidity, with an emphasis on the speed and continuity of trading, and the delay or difficulty of executing an order. Liu (2006) standardised the liquidity measure in order to compare the turnover-adjusted number of zero daily trading volumes across one-, six- and twelve-month periods. As *LMx* is constructed using daily trading volume data, it should not be difficult to use the spirit of the measure to estimate changes in aggregate liquidity across stages in the structure of the trading environment. Unfortunately, as this study focuses on large-capitalisation JSE Top 40 shares, which were chosen based on the fact that they traded every day during the sample period – and thus have no or very few days of zero trading volumes – *LMx* would not meaningfully quantify how liquidity dynamics of the aggregate (Top 40) market have changed over time. Future research methodologies should extend this study to examine a more comprehensive sample, covering a range of firm sizes, trading frequencies and volumes. This would make the use of a measure such as *LMx* more insightful of the overall JSE market trading frequency, as more infrequently-traded shares would be included.

The technological advancement in market microstructure provides a natural experimental setting to test the impact of exogenous liquidity changes on return predictability. Three distinct liquidity regimes should be identifiable: (1) the six-month period prior to 2 July 2012, when all trade moved to the Millennium Exchange platform; (2) the period from 2 July 2012 to 12 May 2014, the date of the launch of the JSE's colocation centre; and (3) the period from 12 May 2014 to June 2016. The *Liq* aggregate liquidity measure, defined in equation (4) above, was used to identify exogenous changes in market liquidity during the three regimes.

3.3 PORTFOLIO CONSTRUCTION AND REGRESSION EVIDENCE

The portfolio of 28 large-capitalisation JSE shares is constructed on a value-weighted basis, in order to calculate portfolio returns. In other words, the portfolio weight attached to each stock is calculated using its firm market capitalisation at the end of the previous year, as a percentage of the total market capitalisation of the share sample. The portfolio was not rebalanced across time, as the constituent shares were selected based on the fact that they traded every day during the sample period, and they were attached portfolio weightings according to their market capitalisations.

One technique to gauge a relation between returns and order imbalances is to compute correlation coefficients between daily returns and order imbalances across liquidity regimes. Note that this does not reveal any *predictive* relation between the two, and thus does not tell us how liquidity directly influences Fama's (1970) market efficiency. Inspired by the methodology of Chordia, Roll and Subrahmanyam (2008), the liquidity-efficiency relation is tested directly using time-series regressions of daily portfolio returns on lagged order imbalances, over all days within a regime.

$$\text{Return}_t = \alpha + \beta_t * OIBR_{t-1} + \varepsilon_t \qquad (5)$$

Where Return_t is the day t return for the portfolio, and $OIBR_{t-1}$ is the order imbalance measure defined above, lagged by one day. If the one-day lagged imbalance measure is a significant predictor of next-period returns (the coefficient, $\beta_{1,}$ is significant), this implies return predictability and thus a deviation from market efficiency.

To determine whether and how efficiency has evolved over time, predictive regressions were performed for each month over the sample. One could infer that the market has become more efficient if the time-series shows a decline in R^2s and t-statistics for stock returns regressed on lagged order imbalances, across the three regimes.

The effect of illiquidity on trading and arbitrage activity should be starker during abnormally illiquid days within a particular liquidity regime. This can be tested by using an explanatory variable in the regressions that interacts the one-day lagged order imbalance measure with a low-liquidity dummy which equals one on days of abnormally low liquidity, and zero otherwise. A day is categorised as low-liquidity if the linearly detrended liquidity indicator for that regime is at least one standard deviation below the expected liquidity indicator.

$$\text{Return}_t = \alpha + \beta_1 * OIB_{t-1} + \beta_2 * (OIB_{t-1} * ILD_t) + \varepsilon_t \qquad (6)$$

Where ILD_t is the low-liquidity dummy and all other variables are as defined above. If the coefficient β_2 on the interaction variable is significantly positive, this would suggest that the predictability of returns from lagged imbalances increases during illiquid periods. Moreover, intertemporal changes in the magnitude and significance of the coefficients on the explanatory variables would provide evidence of whether liquidity improves Fama's (1970) market efficiency.

A further technique used to interpret the possible relation between liquidity and Fama's (1970) efficiency is the Chung and Hrazdil (2010) market efficiency regression. The regression equation (5) was estimated for each sample firm on a monthly basis, using the observations obtained over all days within the month. The resulting R^2s can be interpreted as inverse measures of short-horizon market efficiency (*MktEff*). The relationship running between market efficiency (*MktEff*) and liquidity (*Liq*) can be estimated from the equation:

$$MktEff_i = \alpha + \beta_1 * Regime1_i + \beta_2 * Regime2_i + \beta_3 * Regime3_i + \delta_6 Liq_i + \delta_7 \text{SIZE}_i \qquad (7)$$

Equation (7) is a logit transformation of the *MktEff* measure, the R^2 of each firm-month regression of equation (5), bounded by 0 and 1. Each *Regime* regressor is a binary variable that takes a value of one if the sample month falls within one of the liquidity regimes outlined in Section 3.2 above, and zero otherwise. Liq_i represents the scaled liquidity measure for the firm, averaged across all trades. SIZE is the scaled market capitalisation of the firm at the end of the regression month.

Lastly, Granger causality tests were conducted to understand if there is a causative relationship between aggregate liquidity and market efficiency. The regression of equation (5) was estimated for each month in the sample period, using all days within that month, and the imbalance coefficient was recorded. The daily liquidity indicator, aggregate turnover, was averaged over each month to arrive at a monthly measure. The series of imbalance coefficients and liquidity indicators were then tested for Granger causality. Before performing the Granger causality tests, the two data series were tested for stationarity using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests.

3.4 DEVIATIONS FROM RANDOM WALKS ACROSS LIQUIDITY ENVIRONMENTS

In addition to stock return predictability from order flows, Fama's (1970) financial market efficiency can be assessed through an analysis of deviations from a random walk benchmark.

For a random walk price process, the variance of long-horizon returns is equal to the variance of short-horizon returns multiplied by the number of short intervals in the long horizon (Lo & MacKinlay, 1990). The comparison of short- and long-horizon variance ratios offers an approach to understanding market efficiency by measuring deviations from random walks.

French and Roll (1986) contend that if returns are independent, the variance for a long holding period will equal the cumulated short-horizon variances within that period. This logic dictates that the ratio of the intraday interval variance multiplied by the number of intervals in a day, to the open-to-close midquote return variance of that particular trading day, should converge to one in large samples. Comparing variance ratios across liquidity regimes provides insight into how liquidity influences conformity of midquote prices to random walks. Variance ratios substantially above one are indicative of noise in stock prices. In contrast, increased mispricing in the form of persistent swings away from fundamental values or slow adjustments to shocks could result in variance ratios falling below one (Conrad, Wahal & Xiang, 2015). If the ratio converges to unity over time, this would suggest that lack of return independence, and thus deviations from random walk benchmarks, is reduced in more liquid states of the market when trading is easier, faster and less costly.

In obtaining portfolio variance ratios for each of the three liquidity regimes, the intraday price transaction data (at fifteen-minute intervals) were used to compute short-horizon return variances, which were compared to transaction price return variances from open-to-close of a trading day:

$$\text{Variance ratio} = \frac{(Short-horizon\ return\ variance)*(\#\ short\ horizon\ periods\ in\ long\ horizon)}{Long-horizon\ return\ variance} \quad (8)$$

Variance ratios were averaged across shares in the portfolio (using market capitalisations at the end of the previous year to calculate weights) to obtain the portfolio variance ratios. As noted in Section 3.1, bid-offer quote data were not available at an intraday horizon. It is acknowledged that the use of trade prices exposes the calculation of return variances to inflation due to bid-ask bounce. However, what is relevant in determining deviations from random walks is not absolute values of return variance, but the ratio of short- to long-horizon return variances. Any variance exaggeration is, for the purposes of this analysis, not relevant. What is important is the preservation of consistency in the price convention (trade price versus midquote price) used to compute short-horizon and long-horizon return variances.

3.5 INFORMATIONAL EFFICIENCY

Trading noise can signify deviations from random walks (Chordia, Roll & Subrahmanyam, 2008), but high trading-time *volatility* can be used as a suggestive measure of the amount of private information about fundamentals incorporated into prices. Ratios of (per-hour) open-to-close to close-to-open return variances are a gauge of informational efficiency. Higher variance during market trading hours either signals mispricing or the incorporation of private information into prices through privately informed trading when the market is open (French & Roll, 1986). Each of these explanations has implications for the market efficiency case, in the sense of both Fama (1970) and Shiller (1981; 2003). An analysis of per-hour variance ratios aims to discern whether open-close variances exceed close-open variances, and if so, how this changes across the three liquidity regimes and the possible drivers of the phenomenon. The per-hour variance ratios were obtained by first separating daily firm open-close and close-open returns, and calculating the raw variances of each over the three regimes. Then, the open-close raw variances were divided by the total number of calendar hours that the market was open during the relevant regime, and the same was done for the close-open raw variances (dividing by the total hours that the market was closed during the relevant regime). First-order daily return autocorrelations across liquidity regimes were used in attempting to distinguish between the mispricing and the informed trading arguments in French and Roll (1986). First-order autocorrelations in the squared daily returns were also calculated, given the evidence of nonlinear serial return dependence on the JSE (Babikir *et al.*, 2012; Kruger *et al.*, 2012; Mangani, 2007; McMillan, 2004; Unterhorst, 2014). Nonlinear serial return dependence can be determined by finding significant first-order autocorrelation in the squared daily return series of the portfolio.

Significant autocorrelations are consistent with mispricing due to microstructural frictions or behavioural biases of investors when reacting to new information. However, this does not necessarily imply that mispricing drives the increase in variance ratios over time: one can only conclude that higher relative trading-time variances are a feature of mispricing if the absolute autocorrelations increase along with variance ratios through liquidity regimes. An increase in variance ratios coupled with a decrease in absolute first-order autocorrelations is suggestive of prices adjusting to information about fundamentals, as informed traders find it more worthwhile to transact based on their information when the market is more liquid, and trade is faster, easier and cheaper.

The computation of open-to-close to close-to-open variance ratios makes use of transaction prices to determine return variances. Daily return autocorrelations are determined from end-of-day midquote returns.

4 EMPIRICAL RESULTS

Table 1 reports summary statistics associated with the liquidity, imbalance and return measures for each of the liquidity regimes. The summary statistics are most striking in their incongruence to both the initial hypothesis of this study and to the results of Chordia, Roll and Subrahmanyam (2008). While Chordia *et al.* (2008) report a sharp increase in liquidity (measured by trading cost) during their three regimes, the trend in liquidity on the JSE Top 40 (measured by trading quantity) during 2012 - 2016 is much less apparent. The aggregate liquidity measure, *Liq*, was highest during the six months before the July 2012 platform upgrade, it fell during the almost two years following the upgrade, and it increased slightly during the last regime. Still, aggregate liquidity decreased during the third regime relative to the first regime. This finding is interesting, but contrary to the hypothesis that the structural breaks in the JSE's market microstructure would result in a continuous increase in market liquidity. The result highlights the difficulty in isolating liquidity changes that are due to microstructural factors from those caused by macroeconomic factors and general investor confidence. The average order imbalance has experienced a sharp decline across the three regimes, as has the average daily return (computed using the midpoint of the end-of-day bid-ask quotes). This result is consistent with expectations, as patterns in order flows should mimic patterns in returns given the strong documented imbalance-return relation (Chordia *et al.*, 2008).

Correlation coefficients between daily returns and order imbalances are presented in Table 2. The correlation coefficients in all three regimes are lower than those reported in Chordia *et al*. (2008); however, considering the probable loss of precision due to the use of daily horizons, the correlations are strong. The correlation coefficients become weaker across the three liquidity regimes: they decrease from 31% to 23%.

Table 1: Summary statistics of aggregate liquidity indicators (*Liq* – computed as the weighted average daily turnover across the share sample) and order imbalances (*OIBR*), as well as average daily return measures, by entire sample and by regime.

Entire sample	*Liq* (M)	*OIBR*	Avg. Daily Return
Mean	6.003	0.087	0.045%
Median	5.640	0.105	
Standard deviation	2.348	0.395	
Regime 1			
Mean	6.365	0.147	0.047%
Median	6.157	0.194	
Standard deviation	1.600	0.377	
Regime 2			
Mean	5.828	0.108	0.084%
Median	5.544	0.172	
Standard deviation	2.071	0.386	
Regime 3			
Mean	6.064	0.055	0.010%
Median	5.597	0.056	
Standard deviation	2.678	0.403	

Table 2: Correlation coefficients between daily returns and lagged daily order imbalances, by entire sample and by regime.

Return and *OIBR*	
Entire sample	0.251
Regime 1	0.311
Regime 2	0.275
Regime 3	0.226

Table 3: Predictive regression of daily returns on lagged order imbalances, January 2012 – June 2016.

Dependent variable: Daily Return			
	Coefficient		**t-Statistic**
Intercept	-5.87731E-05		-0.217
OIBR	0.006		8.657***
Adj. R-squared		6.2%	

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

4.1 RETURN PREDICTABILITY

Table 3 presents a basic regression of daily returns on lagged order imbalances, measured by Rands traded, for the entire sample period of January 2012 - June 2016. As in Chordia *et al*. (2005; 2008), *OIBR* is a significant predictor of daily returns. The coefficient on *OIBR* is 0.006, and is highly significant (*t*-statistic of 8.657). The coefficient is also significant in magnitude, given that the average daily return over the sample period is 0.0004 (Table 1). The explanatory power of the regression, at 6.2%, is substantial, given the omission of literally dozens of factors that have been empirically shown to predict returns.

To determine whether and how Fama's (1970) efficiency has evolved over time, predictive regressions were performed for each month over the sample. One could infer that the market has become more efficient if the time-series shows a decline in R^2s and *t*-statistics for stock returns regressed on lagged order imbalances. Figure 1 shows a time-series of the R^2's and *t*-statistics for these regressions. There is no uniform pattern in the significance and explanatory power of *OIBR* in predicting returns. However, there is an unmistakeable downward trend in both the R^2 and *t*-statistic in the eight months following the move to Millennium Exchange in July 2012. Besides this piece of evidence that the trading platform upgrade improved Fama's (1970) market efficiency, the regressions vary from highly significant to insignificant across months in the entire sample period. However, the percentage of statistically significant coefficients in the monthly regressions drops from 33% in Regime 1 to 19% in Regime 3. Similarly, the percentage of R^2's above 13% (the sample average) falls from 50% in Regime 1 to 19% in Regime 3.

The time series of aggregate liquidity (turnover), as well as an annual (12-month) moving average, is plotted in Figure 2. The circled portions of the figure highlight the trends in the moving average of liquidity following the start of the second and third regimes. Although Figure 1 could suggest that the degree of market efficiency improved during the months following the Millennium Exchange migration in July 2012, the aggregate market liquidity trend is too noisy during Regime 2 to make a conclusion about systematic liquidity changes (Figure 2). It should be noted that a general market liquidity improvement following the 2 July 2012 trading engine upgrade was found in Hattingh (2014) and Zito (2014). There is suggestive evidence that the second major structural break, the colocation centre launch, resulted in a continuous increase in market liquidity. Although Figures 1 and 2 do not reveal any obvious trends during the full sample period, the isolation of Regime 3 provides suggestive evidence that the colocation centre launch increased market liquidity, but with no discernible effect on the market efficiency trend.

Figure 1: Market inefficiency trend, JSE Top 40 constituents, 2012 – 2016. Daily return predictions using lagged daily order imbalances.

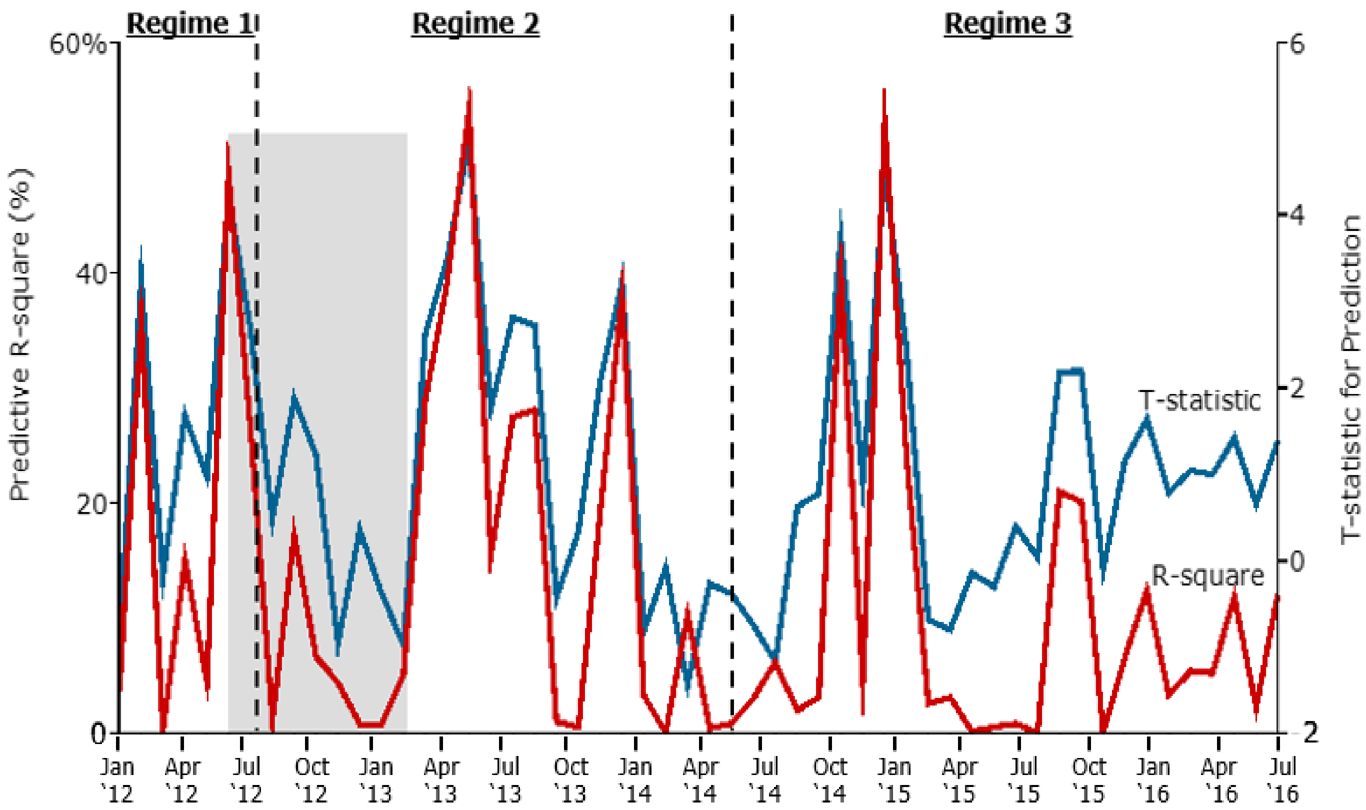
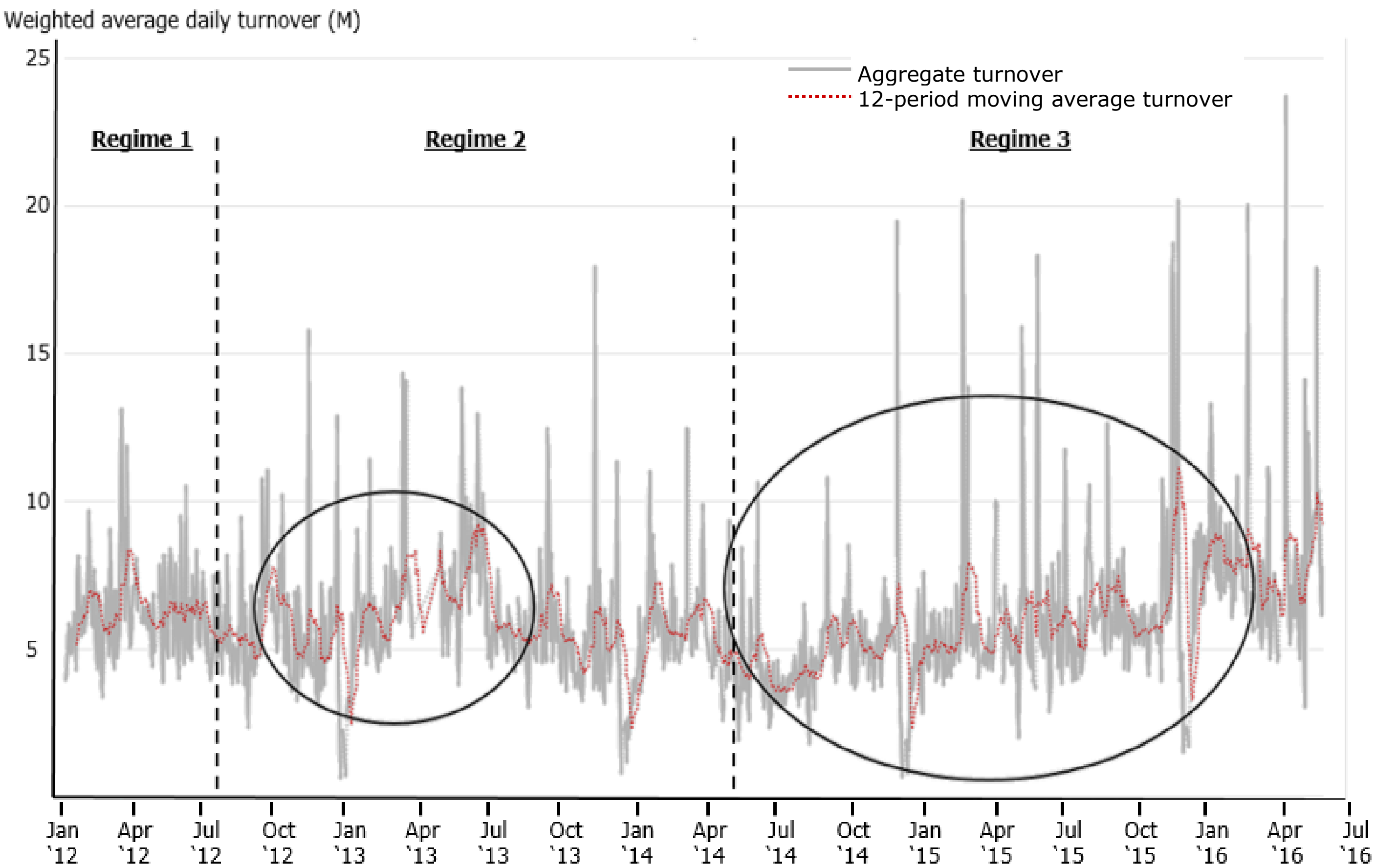


Figure 2: Value-weighted daily aggregate turnover and annual (12-month) moving average, JSE Top 40 constituents, 2012 – 2016.



The liquidity indicator, *Liq*, was stratified by separating liquid days from illiquid ones within each regime. The limiting effect of illiquidity on trading and arbitrage activity should be starker during abnormally illiquid days within a particular liquidity regime (Chordia *et al.*, 2008). A day is categorised as low-liquidity if the linearly detrended liquidity indicator for that regime is at least one standard deviation below the expected liquidity indicator. Table 4 exhibits summary statistics for the liquidity indicator, *Liq*, on low and high liquidity days. The number of illiquid days as a percentage of the total number of trading days is largely constant across the three regimes. The mean liquidity indicator on liquid days is 1.6 times that on illiquid days during Regime 1, but increases to 2.5 times by Regime 3. The insight here is the amplification of the difference in the liquidity indicator on illiquid days relative to normal days during Regimes 2 and 3. This finding prompts the inference that the decreasing trend shown by the liquidity indicator in Table 1 is partly a product of extreme liquidity spikes during the later regimes, a presumption that is supported visually by Figure 2. The standard deviation of the liquidity indicator exhibits a definite increase across the three regimes (Table 1), thus the level of market liquidity was more volatile during the later regimes. Higher volatility in trading quantity on the JSE is a natural consequence of the progressive heightening of political and economic uncertainty in South Africa during the sample period, fuelled by governmental controversies and weak economic indicators. Another potential rationale for the relatively flat liquidity trend over the full sample period is the election of 6 of the 10 top listed JSE firms to pursue dual or primary listings overseas (Gobodo, 2007). This allows foreign investors to trade on their domestic exchanges, and volume traded in these shares on the JSE does not reach the potential levels implied by the utilisation of a faster and more efficient trading platform.

Table 4: Distribution of the liquidity indicator, *Liq*, during liquid and illiquid days, by regime. The ratio calculates the average of *Liq* during liquid days to the average of *Liq* during illiquid days.

		Liq on liquid days (M)	*Liq* on illiquid days (M)	Ratio
Regime 1	Mean	6.632	4.270	1.553
	% of days	91%	9%	
	Number of days	118	12	
Regime 2	Mean	6.113	2.889	2.116
	% of days	91%	9%	
	Number of days	443	42	
Regime 3	Mean	6.308	2.485	2.538
	% of days	92%	8%	
	Number of days	511	43	

Table 5: Predictive regressions of daily returns on lagged order imbalances, and lagged order imbalance interacted with a dummy variable for low-liquidity days within each regime.

		Coefficient		t-Statistic
Regime 1	*OIBR*	0.007		3.741***
	*OIBR*ILD*	-0.007		-0.983
	Intercept	-0.001		-0.743
	Adj. R2		8.9%	
Regime 2	*OIBR*	0.006		6.247***
	*OIBR*ILD*	-0.005		-1.310
	Intercept	0.000		0.440
	Adj. R2		7.5%	
Regime 3	*OIBR*	0.006		5.469***
	*OIBR*ILD*	-0.005		-1.227
	Intercept	0.000		-0.477
	Adj. R2		5.0%	
Entire sample	*OIBR*	0.006		8.879***
	*OIBR*ILD*	-0.005		-1.982**
	Intercept	-8.50231E-05		-0.314
	Adj. R2		6.5%	

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

How does daily liquidity interact with Fama's (1970) market efficiency? This question is addressed by performing the predictive regression of Table 3, with the addition of a low-liquidity dummy (*ILD*) interacted with *OIBR*, in order to estimate the direct influence of liquidity on market efficiency. The low-liquidity dummy is designed to equal one on days of abnormally low liquidity, and zero otherwise. The results of the regressions of daily returns on order imbalances, and the interaction of order imbalances with low-liquidity, are presented in Table 5. For the full sample period, the coefficient on *OIBR* is positive and significant. However, contrary to the results of Chordia *et al.* (2008), the coefficient on the interaction variable, *OIBR*ILD*, is statistically significantly *negative* during the full sample period. This result contradicts the hypothesis that the effect of illiquidity on trading and arbitrage activity would be more pronounced during days of low liquidity. The negative coefficient on

*OIBR*ILD* suggests that the ability of *OIBR* to predict returns weakens during periods of illiquidity. In fact, this ability is almost neutralised. Intriguingly, this same result was found in Chung and Hrazdil (2010) amongst low-volume firms on the NYSE.

The regression results by subperiod show that *OIBR* is always a significant predictor of returns: the *t*-statistic on the coefficient for *OIBR* is 3.74 in Regime 1, increases to 6.25 during Regime 2, and falls to 5.47 during Regime 3. Additionally, the subperiod regressions show that the coefficients on the interaction variables are negative but insignificant for all regimes. The coefficients become more positive from Regime 1 to Regime 3, but the *t*-statistics on the coefficients increase in absolute value across the regimes. Thus, during the later subperiods, illiquidity is a relatively stronger stimulant on the ability of *OIBR* to predict returns. Liquidity seems to reduce market efficiency, albeit less so during the later subperiods. The explanatory power of the regressions has almost halved from Regime 1 to Regime 3, from 9% to 5%.

Overall, the results of Table 5 display a puzzling case for the impact of liquidity on Fama's (1970) market efficiency, but align somewhat with the second hypothesis of Chordia *et al.* (2008). The hypothesis states that if market makers fail to eliminate return predictability by utilizing the information in order flows, traders have incentives to trade on this information. The market is more efficient as a result, but less liquid due to increased adverse selection costs of trade. An interpretation of Figure 2 and Table 5 is that there has not been a perceptible general improvement in market liquidity over the regimes, yet the explanatory power of *OIBR* in predicting returns has decreased over the three regimes. However, *OIBR* remains a significant predictor of returns throughout all regimes. Illiquidity does not inhibit efficiency over the full sample period, but its inhibiting influence increases across regimes. A possible explanation for these findings is the emerging market status of South Africa – although the JSE is a relatively developed capital market, it is still subject to exogenous shocks and contagion effects that tend to plague developing countries during periods of instability. This will naturally have an effect on both market liquidity and price efficiency.

Despite the confounded effect of liquidity on Fama's (1970) market efficiency, the results of Table 5 do confirm the ability of order imbalance to predict next-period returns. This predictability represents an innovative inverse indicator of market efficiency. A robustness check was performed on this finding in order to test its interpretation and reliability. As suggested by Chordia and Subrahmanyam (2004), and echoed in Chordia *et al.* (2008), the predictability of returns from order imbalances may be rooted in autocorrelated imbalances.

The concern may be raised that the results of Table 5 could be affected by the changing behaviour of autocorrelations in the order imbalance series across the three regimes. Before analysing any serial correlation in the *OIBR* series, two types of unit root tests were performed to check for stationarity, as statistical issues arise when analysing non-stationary data. The results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are shown in Table 6. Each test was performed for each regime. For both tests, the null hypothesis is that the series is integrated of order one – it is stationary only after first-differencing. From the results presented in Table 6, in all regimes one can reject the null hypothesis of a unit root (*p*-values equal 0.00). The results confirm that the *OIBR* series is stationary. Table 7 displays first-order serial correlations in *OIBR* for all regimes. The first-order autocorrelations in *OIBR* are insignificant during Regimes 1 and 2, but the first-order autocorrelation is 0.15 during Regime 3, and is highly significant. Thus, the intertemporal behaviour of imbalance autocorrelations does not align with the trends in R^2's and *t*-statistics from the regressions of Table 5. If such imbalance autocorrelations were driving the predictability of returns from imbalances, one would observe an increase in R^2's and *t*-statistics across the regimes. Instead, there is reliable evidence that the opposite transpired for the R^2's as they decrease dramatically across the regimes. The *t*-statistic on the *OIBR* coefficient is highest during Regime 2, yet imbalance autocorrelations were insignificantly different from zero at all lags during this period.

Table 6: Augmented Dickey-Fuller and Phillips-Perron Unit Root Test results on the order imbalance series, Regimes 1, 2 and 3.

Augmented Dickey-Fuller Unit Root Test		
Null Hypothesis: OIBR has a unit root		
	t-Statistic	P-value
Regime 1	-10.373	0.000***
Regime 2	-21.887	0.000***
Regime 3	-19.627	0.000***
Phillips-Perron Unit Root Test		
Null Hypothesis: OIBR has a unit root		
	t-Statistic	P-value
Regime 1	-10.514	0.000***
Regime 2	-22.021	0.000***
Regime 3	-19.774	0.000***

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

Table 7: First-order autocorrelation coefficients for the daily order imbalance series, Regimes 1, 2 and 3.

	Autocorrelation	Q-Stat	P-value
Regime 1	0.048	0.291	0.590
Regime 2	-0.019	0.174	0.677
Regime 3	0.154	12.564	0.000***

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

Table 8: Regression of inverse market efficiency measure on regime indicators, liquidity and size variables.

	Coefficient	Standard Error	t-Statistic	P-value
Intercept	-2.363	0.205	-11.537	1.76675E-29***
Regime 1	0.013	0.180	0.070	0.944
Regime 2	0.250	0.115	2.179	0.030**
Regime 3	-0.028	0.181	-0.153	0.878
LIQ	0.003	0.002	1.456	0.146
SIZE	0.021	0.020	1.075	0.283

Adj. R-squared	0.180%

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

Chung and Hrazdil (2010) explore how a market efficiency measure is affected by liquidity regimes, firm liquidity, and control variables for firm size, volume and trading frequency. The analysis conducted in this research includes a regression aimed to capture the spirit of Chung and Hrazdil's (2010) market efficiency decomposition, but omits control variables for volume, as it exhibits multicollinearity with turnover, and trading frequency, as the sample firms do not vary considerably in terms of trading frequency. The inverse market efficiency measure

(*MktEff*) is the R^2 of firm-month regressions of daily returns on *OIBR*. Note that, when interpreting the inverse market efficiency measure, higher values denote lower levels of market efficiency. This measure was regressed on indicator variables for the liquidity regimes, as well as a size factor, and a firm liquidity indicator. Table 8 presents the output of this regression, which largely corroborates the earlier results in this section. The positive coefficient on the liquidity variable (0.003) indicates that greater liquidity increases market inefficiency, although the coefficient on liquidity is not statistically significant. Consistent with Chung and Hrazdil (2010), firm size is a positive (but insignificant) predictor of market inefficiency (coefficient of 0.021). Chordia and Subrahmanyam (2004) show that order imbalance autocorrelations are greater for larger firms, which they attribute to institutional herding in larger firms. Stronger serial correlation in order imbalances drives stronger return forecastability from order flows, and thus increased market inefficiency.

The coefficients on indicator variables for Regimes 1 and 3 are positive and negative, respectively, although insignificant. This supports the previous result of an intertemporal decrease in power of order imbalance in explaining variation in returns. Interestingly, the coefficient on the indicator variable for Regime 2 is positive, and is the only significant variable in the regression. However, the explanatory power of the market efficiency regression is very low, with an adjusted R^2 of only 0.2%.

An important factor affecting the degree of market efficiency on the JSE is algorithmic trading, which is not accounted for in the regression equation of Table 6. Liquidity is not an effective proxy for algorithmic trading. In Zito (2014), a causative relationship between stock turnover and algorithmic trading could not be established around the time of the 2012 platform upgrade. Hattingh (2014) was unable to prove a correlation between greater algorithmic trading post the 2012 trading engine upgrade, and secular liquidity increases on the JSE. Thus, algorithmic traders, by trading on arbitrage opportunities, could be the unidentified factor explaining the general improvement in market efficiency over time. It is important to separate the effect of algorithmic activity from that of market liquidity in order to understand the drivers of the convergence to market efficiency. This extension is left for exploration in future research.

As a final route in determining whether inefficiency is at all related to liquidity, Granger causality tests were conducted. Regressions of the type in Table 3 were estimated for each month in the sample period, using all days within that month, and the imbalance coefficient was recorded. The daily liquidity indicator, aggregate turnover, was averaged over each month to arrive at a monthly measure. Before performing the Granger causality tests, the two data series were tested for stationarity using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. From the results presented in Table 9, one would reject the null hypothesis that the imbalance coefficient series has a unit root as the *p*-values are essentially zero. Hence the dataset is stationary. However, for the aggregate turnover series in Table 10, the null hypothesis of non-stationarity cannot be rejected as the *p*-values are 0.18 (ADF test) and 0.22 (PP test). The turnover series was thus first differenced, and it can be seen from Table 10 that the series of first differences in turnover is stationary as the *p*-values are essentially zero for both the ADF test and the PP test. Thus, the Granger causality tests were performed using the measures of inefficiency (the imbalance coefficient), and the first difference in turnover, which can be interpreted as a measure of monthly changes in liquidity.

The results of the Granger causality tests for the full sample period, and for each regime, are shown in Table 11. It is generally better to use more rather than fewer lags in the test regressions when performing Granger causality tests. Six lags were used in most regressions, however, due to fewer available observations in Regime 1, one lag was used in the test regression for Granger causality during this regime. The full sample period results confirm that there is no causative relationship running from liquidity changes to the inefficiency measure – the *p*-value for the null hypothesis that the change in aggregate turnover does not Granger-cause the imbalance coefficient is 0.39, thus the null hypothesis cannot be rejected. The reverse null hypothesis that the coefficient does not cause the change in aggregate turnover measure also cannot be rejected. The results are similar for each liquidity regime, but for one seemingly peculiar result in the Regime 1 results. The *p*-value for the null hypothesis that the coefficient does not cause the change in aggregate turnover is 0.01 for Regime 1, which seems to suggest a causative relationship running from the market inefficiency measure to changes in aggregate liquidity. Nonetheless, caution should be used when interpreting this result due to the small number of observations in the subsample. In sum, there is no evidence of econometric causality running from changes in aggregate liquidity to the market inefficiency measure, proxied by the coefficient in the regression of daily returns on order imbalances. On the JSE, liquidity has very little influence on the convergence to market efficiency.

<u>Table 9: Augmented Dickey-Fuller and Phillips-Perron Unit Root Test results on the order imbalance coefficient series, Entire Sample.</u>

Augmented Dickey-Fuller Unit Root Test		
Null Hypothesis: Series has a unit root		
	t-Statistic	P-value
Entire Sample	-4.908	0.001***
Phillips-Perron Unit Root Test		
Null Hypothesis: Series has a unit root		
	t-Statistic	P-value
Entire Sample	-4.925	0.001***

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

<u>Table 10: Augmented Dickey-Fuller and Phillips-Perron Unit Root Test results on the aggregate turnover and first difference series, Entire Sample.</u>

Augmented Dickey-Fuller Unit Root Test		
Null Hypothesis: Series has a unit root		
	t-Statistic	P-value
Aggregate turnover series, Entire Sample	-2.883	0.176
First difference in aggregate turnover series, Entire Sample	-5.737	0.000***
Phillips-Perron Unit Root Test		
Null Hypothesis: Series has a unit root		
	t-Statistic	P-value
Aggregate turnover series, Entire Sample	-2.747	0.223
First difference in aggregate turnover series, Entire Sample	-12.401	0.000***

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

Table 11: Granger causality test results of market liquidity (proxied by the first difference in aggregate turnover) and market inefficiency (proxied by order imbalance coefficient in monthly regression of daily returns on order imbalances), Entire Sample and by regime.

Entire Sample		
Null Hypothesis	**F-Statistic**	**P-value**
Liquidity does not Granger Cause Efficiency	1.080	0.394
Efficiency does not Granger Cause Liquidity	0.198	0.975
Regime 1		
Null Hypothesis	**F-Statistic**	**P-value**
Liquidity does not Granger Cause Efficiency	0.301	0.680
Efficiency does not Granger Cause Liquidity	1913.900	0.014**
Regime 2		
Null Hypothesis	**F-Statistic**	**P-value**
Liquidity does not Granger Cause Efficiency	0.439	0.818
Efficiency does not Granger Cause Liquidity	0.992	0.646
Regime 3		
Null Hypothesis	**F-Statistic**	**P-value**
Liquidity does not Granger Cause Efficiency	1.002	0.499
Efficiency does not Granger Cause Liquidity	0.366	0.877

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level

4.2 DEVIATIONS FROM RANDOM WALKS ACROSS LIQUIDITY ENVIRONMENTS

Under Fama's (1970) EMH, an efficient market is one in which investors cannot expect to realise arbitrage profits from trading strategies. The previous section focuses on return predictability from order flows as an inverse measure of Fama's (1970) market efficiency, but does not address whether prices follow a random walk. This section uses a comparison of short- and long-horizon variance ratios as an assessment of whether deviations from a random walk (and thus from an efficient market benchmark, in Fama's (1970) sense) have changed over the liquidity regimes. Deviations from a random walk can emerge because the market maker's inventory control activity prompts serial correlation in returns. If algorithmic traders help the market maker to absorb outside orders, such deviations would diminish. There should be smaller deviations from a random walk price process when trading is more infused with algorithmic activity.

The ratio of fifteen-minute to open-to-close midquote return variances for each regime are presented in Table 12. A random walk process prescribes a variance ratio of unity. The variance ratios across the regimes signal a significant amount of noise in stock prices: the short-horizon variance ratio is two to three times greater than that of the long horizon. Prices do not follow a random walk in any of the regimes. However, the degree of noise created by the trading process decreases between Regime 1 and 3: the ratio is 2.74 in Regime 1, increases slightly to 2.88 in Regime 2 (although the difference between the ratios in Regimes 1 and 2 is statistically insignificant), and decreases to 2.06 during Regime 3. The *p*-value for a one-tail *t*-test on the variance ratios for Regimes 2 and 3 is below 0.05, thus one can safely state that the variance ratios in Regime 3 are significantly lower relative to those in Regime 2. The evidence accords with that of the preceding analysis: the JSE Top 40 has become more efficient over the sample period, as prices have converged more closely to a random walk process. Given the evidence in Zito (2014) and Hattingh (2014), this period coincides with a proliferation of algorithmic trading on the JSE. Algorithmic traders are more likely to recognise profitable price patterns and arbitrage opportunities, and by exploiting them, bring prices closer to efficient market benchmarks.

Table 12: Ratios of fifteen minute return variance to open-to-close return variance (scaled by the number of fifteen minute intervals in a day), by regime.

	Regime 1	Regime 2	Regime 3
Variance Ratio	2.74	2.88	2.06
		Regime 1 and 2	Regime 2 and 3
P-value for differences across regimes		0.258	0.041**

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

4.3 INFORMATIONAL EFFICIENCY

The preceding pieces of analysis have focused on proving a case for the convergence to market efficiency, where market efficiency has implicitly been characterised in the sense of Fama (1970): a lack of return predictability, and conformity to a random walk price process. As has been emphasised throughout this study, market efficiency can also be set within the realm of the microstructure literature, inspired by Shiller (1981; 2003). This second arm of 'two-pronged efficiency', termed informational efficiency, considers the degree to which asset prices reflect private information about firm fundamentals as a gauge of market efficiency.

Chordia, Roll and Subrahmanyam (2008) hypothesise that improved informational efficiency should be a consequence of greater market liquidity. In the context of that paper, a smaller tick size allows market participants to trade on ever-smaller pieces of information, and it is expected that informed trading will increase as the tick size decreases. The authors use the French and Roll (1986) ratio of open-to-close to close-to-open return variances to test this hypothesis. French and Roll (1986) find that this ratio is substantially greater than one, implying more price volatility when the market is open. Three potential explanations are considered: (1) volatility is caused by the incorporation of private information when informed traders trade; (2) volatility is caused by pricing errors due to investor behavioural factors or market frictions and microstructure noise; and (3) volatility is caused by public information arriving during business hours. French and Roll (1986) reject (3) as variance ratios are not significantly different during business days when the exchange is closed. Therefore, the variance ratio can be related either to mispricing or the amount of private information incorporated into prices. The aim of this section is to assess whether variance ratios have changed during the course of the three liquidity regimes, and whether any discernible pattern of changes reveals which of the two potential explanations expressed by French and Roll (1986) is dominant. Table 13 reports the open-to-close/close-to-open per-hour variance ratios for the three regimes. Consistent with French and Roll (1986), all variance ratios indicate that price volatility is much higher during trading hours than during non-trading hours. A one-tailed *t*-test confirms that this difference is significant: the *p*-value for the null hypothesis that open-close volatility does not exceed close-open volatility is close to zero (0.0005), therefore the null hypothesis can be rejected. There is a very high statistical probability that trading-time volatility far exceeds non-trading time volatility.

The trading-versus-non-trading variance ratios for Regimes 1, 2 and 3 are 1.06, 8.82, and 6.62, respectively. The *p*-values from one-tailed *t*-tests indicate that these differences are statistically significant. As in Chordia *et al.* (2008), the variance ratio increases between Regimes 1 and 3. However, the ratio decreases between Regimes 2 and 3. It is acknowledged that these data points are insufficient to reach a conclusion on how trading-versus-non-trading variance has changed across the sample period. Additionally, external factors such as adjustments in US Federal Reserve policy could have influenced the relationship between trading-time and non-trading time volatility on the JSE. The results are thus to be interpreted with caution.

What could be the phenomenon causing excess trading-time volatility? French and Roll (1986) use first-order daily return autocorrelations to distinguish between the mispricing argument and the informed trading argument. They surmise that the absolute autocorrelation level is positively related to mispricing in the form of microstructural frictions or investor behavioural factors such as misreaction to information. Thus, an examination of first-order daily return autocorrelations offers suggestive evidence of the driving phenomenon behind the high variance ratios, and why they have fluctuated across the regimes. Prior to the analysis of daily return autocorrelations, Augmented Dickey-Fuller and Phillips-Perron tests were performed to check for stationarity in the daily return series. Table 14 presents the ADF and PP test results for the daily return series of each regime. The null hypothesis of non-stationarity can be rejected for all regimes: the *p*-values are below 0.05 for all of the ADF and the PP tests. Therefore the daily return series is stationary for all regimes. Table 15 presents first-order autocorrelations for the daily return series in each regime. The first-order daily return autocorrelation is negative and insignificant in all cases. The first-order autocorrelation decreases in absolute value (in other words, it tends closer to zero) across the regimes: from -0.072 in Regime 1, to -0.034 in Regime 2, and to -0.004 in Regime 3. Nonetheless, all of the first-order autocorrelations are insignificant. There is no evidence of first-order autocorrelation in the daily stock returns during any regime. This finding is consistent with Babikir *et al.* (2012). However, there is strong evidence for significant higher order return autocorrelations during Regimes 1 and 2 (shown in Appendix III).

Table 13: Ratios of open-to-close/close-to-open per-hour return variances, by regime.

	Regime 1	Regime 2	Regime 3
Variance Ratio	1.06	8.82	6.62
		Regime 1 and 2	Regime 2 and 3
P-value for differences between regimes		0.000***	0.003***
P-value for differences in open-close volatility versus close-open volatility over all regimes	0.000***		

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

Table 14: Augmented Dickey-Fuller and Phillips-Perron Unit Root test results on the daily return series, Regimes 1, 2 and 3.

Augmented Dickey-Fuller Unit Root Test		
Null Hypothesis: Daily return series has a unit root		
	t-Statistic	P-value
Regime 1	-10.489	0.000***
Regime 2	-22.715	0.000***
Regime 3	-23.279	0.000***
Phillips-Perron Unit Root Test		
Null Hypothesis: Daily return series has a unit root		
	t-Statistic	P-value
Regime 1	-12.236	0.000***
Regime 2	-22.852	0.000***
Regime 3	-23.326	0.000***

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

Table 15: First-order autocorrelation coefficients for the daily return series, Regimes 1, 2 and 3.

	Autocorrelation	Q-Stat	P-value
Regime 1	-0.072	0.684	0.408
Regime 2	-0.034	0.557	0.455
Regime 3	-0.004	0.007	0.932

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

There is ample evidence of nonlinear stock return dependencies on the JSE (Babikir *et al.*, 2012; Kruger *et al.*, 2012; Mangani, 2007; McMillan, 2004; Unterhorst, 2014). Given the evidence of nonlinear serial return behaviour, as well as linear serial dependence not being a necessary condition for nonlinear serial dependence (Hinich & Lim, 2008), it was thought prudent to examine autocorrelations in the squared stock returns. Nonlinear reverting patterns in returns, in the form of positive-return persistence through time, are captured through autocorrelations of squared (absolute) returns (Babikir *et al.*, 2012). Before analysing correlograms, ADF and PP tests were performed on the squared returns series for all regimes, in order to test for stationarity. The results of the unit root tests are presented in Table 16. All of the ADF tests and the PP tests confirm that the squared returns series are stationary for all regimes: the *p*-values are below 0.05 for all tests. The first-order autocorrelations for the squared returns series in each regime are presented in Table 17. From Table 17, it is evident that there was no nonlinear serial dependence during Regimes 1 and 2, as the autocorrelation statistics are insignificant. Yet the results for Regime 3 show that there was significant nonlinear serial dependence in the return series. Nonlinear serial dependence has become stronger across the three regimes. These episodic incidences of nonlinear serial dependence support Kruger *et al.* (2012), who find evidence of significant nonlinear serial dependence for JSE shares, the occurrence of which is episodic in nature.

The variance ratio provides evidence on the informational efficiency of the pricing system in the essence of Kyle (1985). During Regime 1, trading-time return variance was roughly one-for-one with return variance during non-trading hours. The ratio of trading-time to non-trading time return variance experienced a great rise between Regimes 1 and 2, but significantly decreased between Regimes 2 and 3. The latter trend was coupled with a surge in nonlinear serial dependence. The lower relative trading-time variance during Regime 3 is evidently due to a higher degree of positive-return persistence during the latest regime. Thus, it cannot be concluded that the latest regime facilitated a greater degree of informational efficiency. It is proposed that the existence of positive-return persistence during the most recent regime could be due to investor misreaction to information, and/ or microstructural frictions such as increased adverse selection costs. The possibility of increased adverse selection costs during the later regimes was also inferred in Section 4.1.

The consideration of nonlinear processes is essential when assessing weak-form market efficiency on the JSE. An examination of linear serial return dependence in Table 15 seems to suggest a lack of first-order daily return autocorrelation on the JSE. Yet, Table 17 confirms the existence of nonlinear serial return dependence, which can arise due to microstructure effects; nonlinear feedback mechanisms in price movements; transaction costs and investor behavioural biases (Antoniou, Ergul & Holmes, 1997). As in Kruger *et al.* (2012), there are only intermittent periods of linear or nonlinear serial return dependence on the JSE. Note that this does not necessarily negate the weak-form efficiency of the stock market, in the spirit of Fama (1970), as return dependence is intertemporally inconsistent and thus may not be easily predictable and economically exploitable over time.

It was shown in Sections 4.1 and 4.2 that over the sample period 2012 – 2016, JSE Top 40 returns experienced a reduction in predictability from order flows, as well as a closer convergence to a random walk benchmark. Nevertheless, JSE Top 40 prices became less informationally efficient. It is possible for a market to move toward fulfilment of the Fama (1970) criteria for market efficiency, but for its constituent asset prices to simultaneously become less representative of fundamental firm value.

Table 16: Augmented Dickey-Fuller and Phillips-Perron Unit Root test results on the squared daily return series, Regimes 1, 2 and 3.

Augmented Dickey-Fuller Unit Root Test		
Null Hypothesis: Squared daily return series has a unit root		
	t-Statistic	P-value
Regime 1	-11.353	0.000***
Regime 2	-3.493	0.041**
Regime 3	-12.951	0.000***
Phillips-Perron Unit Root Test		
Null Hypothesis: Squared daily return series has a unit root		
	t-Statistic	P-value
Regime 1	-11.362	0.000***
Regime 2	-22.928	0.000***
Regime 3	-20.729	0.000***

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

Table 17: First-order autocorrelation coefficients for the squared daily return series, Regimes 1, 2 and 3.

	Autocorrelation	Q-Stat	P-value
Regime 1	0.019	0.049	0.825
Regime 2	0.065	2.053	0.152
Regime 3	0.167	15.612	0.000***

Note: (*) Indicates statistical significance at the 10% level; (**) indicates statistical significance at the 5% level; (***) indicates statistical significance at the 1% level.

4.4 SUMMARY OF RESULTS

The analyses carried out in this study have aimed to (1) introduce a new inverse measure of market efficiency i.e. return predictability from order imbalances that has been hitherto unexplored in the South African literature; (2) understand the inverse efficiency measure's time variation and relation to liquidity; and (3) provide a degree of reconciliation of Fama's (1970) definition of market efficiency to that of Shiller (1981; 2003).

Uniquely to the South African literature, this study has proven that order imbalances are a significant predictor of daily returns, and, although the significance of the predictability has decreased somewhat over time, it remains strongly embedded in JSE returns data. A proposed rationale for this return predictability from order imbalances is limited market making capacity: market makers make incomplete adjustments to, or misreact to information contained in asymmetric order flows.

Contrary to international studies, the relationship between market efficiency and liquidity on the JSE is less clear-cut. An examination of an aggregate turnover measure for liquidity shows that, although hypothesised that liquidity would generally increase after the structural breaks marking Regimes 2 and 3, there has not been a long-term upward trend in aggregate liquidity. While there was an uptick in liquidity after the second structural break denoting the start of Regime 3, increased volatility in liquidity prevented a systematic increase in market liquidity during the third regime. Regressions of daily returns on order imbalances that include dummy variables for illiquid days within each regime confirm that illiquidity is unable to enhance the ability of order imbalances to predict returns.

Thus, unlike international studies, it cannot be concluded that liquidity aids in the convergence to market efficiency (in the Fama (1970) sense). Moreover, in a regression of an inverse market efficiency measure (the R^2 of firm-month regressions of daily returns on order imbalances) on regime indicators and factors for stock liquidity and size, only one of the independent variables, the Regime 2 indicator regressor, is a significant predictor of market inefficiency. The factors affecting market efficiency on the JSE remain unknown, although it is proposed that algorithmic trading could be one of these missing factors. As established in Hattingh (2014) and Zito (2014), the Millennium Exchange upgrade was strongly associated with higher levels of algorithmic activity, but not necessarily with increased liquidity. A potential interpretation of the results in this study is that the trading platform upgrade facilitated a rush of algorithmic traders, who are more likely to trade on price patterns such as those arising from information in order flows. Market efficiency improved, but exogenous factors, such as systematic emerging market instability, have a confounding effect on market liquidity. The JSE Top 40's conformity to Fama's (1970) EMH has been evidenced through reduced return predictability from order imbalances, as well as improved adherence to a random walk benchmark, measured by short-to-long-horizon variance ratios. Over the three regimes, the JSE Top 40 has become more efficient in the spirit of Fama's (1970) EMH.

As championed by Shiller (1981; 2003) and in the rich microstructure literature (Bagehot, 1971; Campbell & Kyle, 1993; Kyle, 1985; Poterba & Summers, 1988), informational efficiency, or the degree to which prices reflect information about firm fundamentals, is also an indicator of financial market efficiency. A comparison of trading-time versus non-trading time return variances shows that excess volatility during trading hours decreases across Regimes 2 to 3. This result is coupled with a strong emergence of nonlinear serial return dependence, which is indicative of greater mispricing due to traders' behavioural biases or trading frictions. Thus, informational efficiency decreased during the course of the three regimes. The infusion of algorithmic trading following the 2012 platform upgrade likely reduced the pervasiveness of price patterns through more reliable recognition and exploitation of these patterns. However, it is suggested that algorithmic trading has not brought about more accurate pricing of information on firm fundamentals. In fact, it could be inferred that mispricing increased after the platform upgrade, whether due to traders' misreaction to information or market frictions such as adverse selection costs.

4.5 LIMITATIONS AND EXTENSIONS TO THIS STUDY

The aim of the Chordia *et al*. (2008) work was to gauge the link between liquidity and intraday market efficiency. The authors emphasise intraday intervals as inefficiencies are not likely to persist over daily horizons. As mentioned earlier, the data availability constraints encountered during this study have limited the research in two important ways: first, the use of daily data for the return predictability regressions restricts precision in detecting price patterns representing market inefficiency; and second, the four-year sample period means that certain important structural breaks in the evolution of the JSE's market liquidity have not been included in the analysis (most notably, the 1996 move to an automated trading platform). The liquidity regimes are also not entirely comparable in terms of length: for example, Regime 1 contains just six months of data, while Regime 2 contains 22 months, and Regime 3, 26 months.

Despite the theoretical loss of precision in detecting deviations from market efficiency, this study has proven that return predictability from past information does arise and persist at a daily horizon. An interesting avenue for future research is whether this return predictability is economically exploitable, specifically, whether it is possible to earn an abnormal profit by trading on the order imbalance. Confirmation of inefficiency requires a demonstration that returns can consistently outperform those of a buy-and-hold strategy of comparable risk.

This study has focused on a small sample of JSE Top 40 shares, all of which have large market capitalisations and high trading frequencies. A worthwhile extension of this research would be to include a larger and more diverse sample of shares, spanning firms of all sizes. In light of Chung and Hrazdil's (2010) assertion that short-horizon return predictability from past order flows varies significantly across portfolios stratified by firm size, trading frequency, and trading volume, it is recommended that controls for these factors be applied in cross-sectional research designs.

One of the conclusions to this study was that the structural breaks prompted algorithmic activity to infuse daily trade, which lowered return predictability from past order imbalances. Although previous South African studies have confirmed the correlation between the trading platform upgrade and increased algorithmic activity, this study has provided no direct evidence of a positive association between algorithmic activity and market efficiency. Future studies should include a proxy for algorithmic trading in order to understand the predictors of the inverse market efficiency measure.

Finally, this study has used a measure of aggregate turnover as a proxy for market liquidity. Future studies should compare these results to those obtained using other liquidity measures, especially the multidimensional liquidity metric of Liu (2006), which should capture greater liquidity variation in smaller firms due to trading speed, continuity and ease of trade.

5 CONCLUSIONS

The theory of efficient markets has incredible importance in the field of finance. Its validity has preoccupied financial economists and practitioners for decades. Fama's (1970) Efficient Markets Hypothesis describes an efficient market as one that is sufficiently competitive so as to eliminate the expectation of realising an arbitrage profit from trading strategies, excluding transactions costs. It follows that asset returns should not be predictable from past, public or private pertinent information, corresponding to weak-, semi-strong- and strong-form market efficiency. If prices update rapidly on the arrival of new information, price changes should express the same randomness as the arrival of new information. Operating in parallel to the Fama (1970) definition is the market efficiency characterisation of Shiller (1981; 2003). Under Shiller (1981; 2003), an efficient financial market is one in which asset prices mirror the fundamental values of the assets, and movements in asset prices are rooted in new information about fundamental values. One of the aims of this study has been to find a point of intersection for these parallel ideas.

The primary aim of this study was to establish whether a relationship exists between greater market liquidity and a convergence to market efficiency, where market efficiency is demarcated by both Fama (1970) and Shiller (1981; 2003). Market liquidity is proxied by a weighted average measure of aggregate share turnover. Exogenous structural breaks corresponding to supposed increases in market liquidity levels were identified, corresponding to the trading platform upgrade in July 2012, and the colocation facility launch in May 2014. These structural breaks denote the bounds of the three liquidity regimes. It was hypothesised that these structural breaks represent improvements in market microstructure, enabling easier, faster and less costly trading, which in turn should be related to price formation and behaviour. Specifically, a more liquid market should be more efficient because astute traders can more readily exploit return predictability, mispricing and/ or their superior information, thereby facilitating a convergence to market efficiency. An understanding of the relationship between market structure, liquidity and price behaviour has implications for the theory of how prices aggregate information, as well as for practical policy purposes.

In evaluating the link between liquidity and market efficiency, tests were carried out on both the Fama (1970) and Shiller (1981; 2003) definitions of market efficiency. The hypothesis was that liquidity would influence both of these channels: it encourages arbitrage trading, which diminishes return predictability; and it encourages trading on incremental pieces of private information, which brings prices closer to full-information values.

The first part of the analysis showed that return predictability from past order imbalances does exist in the share sample. This predictability is economically substantial and persistent through time, although its significance has decreased somewhat across the three regimes. Surprisingly, this predictive relation is not influenced by liquidity. Extensive tests of a direct relationship between liquidity and return predictability could not confirm the existence of such a relationship. Predictive regressions of returns on order imbalances, with the addition of an interaction dummy variable capturing days of abnormally low liquidity within each regime, were performed for each liquidity subperiod. The insignificant coefficients contradict the hypothesis that the ability of order imbalances to predict returns should be amplified during illiquid periods within each regime. If anything, the coefficient on the interaction variable is significantly negative during the full sample period, suggesting that the predictability of returns from order flows weakens during periods of illiquidity. In a separate regression of an inverse measure of market efficiency on indicator variables for each regime, as well as on liquidity and size factors, liquidity has no predictive relationship with efficiency. The influence of liquidity on return predictability is insignificant, and an unknown factor seems to be driving changes in this predictability over time. It is proposed that, in partial accordance with expectations, the structural breaks encouraged an infusion of algorithmic trade, which improved market efficiency, but confounding effects such as exogenous market shocks prevented a general increase in liquidity.

The second piece of analysis, of short- to long-horizon variance ratios, signalled a significant amount of noise in stock prices: prices did not follow a random walk price process during any of the regimes. However, consistent with the general decline in return predictability across the regimes, prices are significantly closer to a random walk benchmark during the most recent regime relative to the earlier ones. In aggregate, the evidence supports the hypothesis that increased algorithmic trading activity enhances market efficiency by reducing return predictability, but there is no evidence to support the hypothesis that market liquidity is associated with enhanced market efficiency.

The first two pieces of analysis in this study focused on proving the convergence to the Fama (1970) idea of market efficiency, which implies a lack of return predictability. In parallel to the Fama (1970) definition is that of Shiller (1981; 2003), which is the definition embraced by the microstructure literature. Termed informational efficiency, this definition considers the amount of private information about firm fundamentals reflected in asset prices. The hypothesis here was that liquidity encourages trading on private information as it allows smart investors to trade large quantities quickly, at low cost, with little price impact. This enhances informational efficiency by bringing prices closer to fundamental or full-information values. In consideration of this definition of market efficiency, ratios of per-hour open-close to close-open volatility were analysed in conjunction with first-order daily return autocorrelations. Trading-time volatility is much greater than non-trading time volatility during the later regimes, but the relative difference decreases across the later regimes. This could suggest that the phenomenon causing excess trading-time volatility to arise dissipates from Regime 2 to Regime 3.

An investigation of first-order daily return autocorrelations, as well as tests of nonlinear serial return dependencies sheds light on the possible driving factors behind high trading-time variances. The first-order daily return autocorrelation decreases in absolute value across the regimes, but it is insignificantly different from zero across all regimes. At face value, this seems to suggest that the observed decrease in the trading-time/ non-trading time variance ratio is not due to changes in the degree of mispricing of JSE Top 40 shares. Nevertheless, given the vast amount of empirical evidence of nonlinear stock return dependencies on the JSE, tests were conducted for such nonlinear dependencies in each regime.

Consistent with previous South African studies, it was found that nonlinear serial return dependencies are episodic in nature, and are stronger during the more recent regime. The significant decline in the trading-time/ non-trading time variance ratio across the later regimes, coupled with the surge in nonlinear serial return dependence, suggests that positive-return persistence during the later regime has reduced relative trading-time volatility. Positive-return persistence can manifest due to investor misreaction to information, and/ or microstructural frictions such as increased adverse selection costs.

Thus, while prices have become less predictable over time, the JSE Top 40 index has become less informationally efficient. While the structural breaks have not necessarily facilitated a general increase in market liquidity, they have stimulated more algorithmic trade (Hattingh, 2014; Zito, 2014). Algorithmic traders have likely reduced the pervasiveness of price patterns through more reliable recognition and exploitation of these patterns. However, these traders do not transact on information about firm fundamentals, and thus do not engender a higher degree of informational efficiency.

As proposed in Section 2.1.1, it is conceivable for the stock price to be weak-form efficient according to Fama (1970) - it cannot be predicted from past public information - but at the same time to be incorrectly valued, as there is some information about fundamental value that is not reflected in the price. This study has shown that over three microstructural regimes, the JSE Top 40 has become more weak-form efficient in the spirit of Fama's (1970) EMH, but informational efficiency has deteriorated. The ideas of Fama (1970) and Shiller (1981; 2003), of what constitutes an efficient market, have hopefully moved one step closer toward a unified theory of market efficiency. Importantly, efficiency is not an infallible state of a market, but a process. Either or both meanings of efficiency may prevail at any time, and they should be viewed as complementary, but independent. Tests of return predictability or conformity to random walk benchmarks should be incomplete without tests of informational efficiency, and vice versa.

The contribution of this study to the field is threefold: it introduces a new inverse measure of market efficiency – return predictability from order imbalances - previously unexplored in the South African literature; it provides insight into the measure's time variation and relation to liquidity; and it takes a step toward understanding how the ideas of Fama (1970) and Shiller (1981; 2003) can both hold independently and inform one another.

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7 APPENDIX I

Table A1: Augmented Dickey-Fuller Unit Root Test results on the order imbalance series, Regime 1.

Null Hypothesis: OIBR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.37295	0.0000
Test critical values:	1% level	-4.034356	
	5% level	-3.446765	
	10% level	-3.148399	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OIBR)
Method: Least Squares
Date: 01/14/17 Time: 12:00
Sample (adjusted): 1/04/2012 6/29/2012
Included observations: 123 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIBR(-1)	-0.955369	0.092102	-10.37295	0.0000
C	0.180805	0.071410	2.531917	0.0126
@TREND("1/03/2012")	-0.000617	0.000972	-0.634628	0.5269

R-squared	0.472803	Mean dependent var	0.007196
Adjusted R-squared	0.464016	S.D. dependent var	0.521071
S.E. of regression	0.381481	Akaike info criterion	0.934575
Sum squared resid	17.46330	Schwarz criterion	1.003164
Log likelihood	-54.47633	Hannan-Quinn criter.	0.962436
F-statistic	53.80940	Durbin-Watson stat	1.982535
Prob(F-statistic)	0.000000		

Table A2: Phillips-Perron Unit Root Test results on the order imbalance series, Regime 1.

Null Hypothesis: OIBR has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-10.51374	0.0000
Test critical values:	1% level	-4.034356	
	5% level	-3.446765	
	10% level	-3.148399	

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

Residual variance (no correction)	0.141978
HAC corrected variance (Bartlett kernel)	0.174725

Phillips-Perron Test Equation
Dependent Variable: D(OIBR)
Method: Least Squares
Date: 01/29/17 Time: 15:25
Sample (adjusted): 1/04/2012 6/29/2012
Included observations: 123 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIBR(-1)	-0.955369	0.092102	-10.37295	0.0000
C	0.180805	0.071410	2.531917	0.0126
@TREND("1/03/2012")	-0.000617	0.000972	-0.634628	0.5269

R-squared	0.472803	Mean dependent var	0.007196
Adjusted R-squared	0.464016	S.D. dependent var	0.521071
S.E. of regression	0.381481	Akaike info criterion	0.934575
Sum squared resid	17.46330	Schwarz criterion	1.003164
Log likelihood	-54.47633	Hannan-Quinn criter.	0.962436
F-statistic	53.80940	Durbin-Watson stat	1.982535
Prob(F-statistic)	0.000000		

Table A3: Augmented Dickey-Fuller Unit Root Test results on the order imbalance series, Regime 2.

Null Hypothesis: OIBR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-21.88716	0.0000
Test critical values:	1% level	-3.978133	
	5% level	-3.419621	
	10% level	-3.132420	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OIBR)
Method: Least Squares
Date: 01/14/17 Time: 12:03
Sample (adjusted): 7/03/2012 5/09/2014
Included observations: 460 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIBR(-1)	-1.023409	0.046758	-21.88716	0.0000
C	0.154537	0.036763	4.203639	0.0000
@TREND("7/02/2012")	-0.000188	0.000136	-1.381078	0.1679

R-squared	0.511777	Mean dependent var	0.000531
Adjusted R-squared	0.509640	S.D. dependent var	0.551733
S.E. of regression	0.386355	Akaike info criterion	0.942378
Sum squared resid	68.21632	Schwarz criterion	0.969321
Log likelihood	-213.7469	Hannan-Quinn criter.	0.952987
F-statistic	239.5239	Durbin-Watson stat	1.995783
Prob(F-statistic)	0.000000		

Table A4: Phillips-Perron Unit Root Test results on the order imbalance series, Regime 2.

Null Hypothesis: OIBR has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-22.02100	0.0000
Test critical values:	1% level	-3.978133	
	5% level	-3.419621	
	10% level	-3.132420	

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

Residual variance (no correction)	0.148296
HAC corrected variance (Bartlett kernel)	0.123390

Phillips-Perron Test Equation
Dependent Variable: D(OIBR)
Method: Least Squares
Date: 01/29/17 Time: 15:27
Sample (adjusted): 7/03/2012 5/09/2014
Included observations: 460 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIBR(-1)	-1.023409	0.046758	-21.88716	0.0000
C	0.154537	0.036763	4.203639	0.0000
@TREND("7/02/2012")	-0.000188	0.000136	-1.381078	0.1679

R-squared	0.511777	Mean dependent var	0.000531
Adjusted R-squared	0.509640	S.D. dependent var	0.551733
S.E. of regression	0.386355	Akaike info criterion	0.942378
Sum squared resid	68.21632	Schwarz criterion	0.969321
Log likelihood	-213.7469	Hannan-Quinn criter.	0.952987
F-statistic	239.5239	Durbin-Watson stat	1.995783
Prob(F-statistic)	0.000000		

Table A5: Augmented Dickey-Fuller Unit Root Test results on the order imbalance series, Regime 3.

Null Hypothesis: OIBR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-19.62720	0.0000
Test critical values:	1% level	-3.975532	
	5% level	-3.418354	
	10% level	-3.131670	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OIBR)
Method: Least Squares
Date: 01/14/17 Time: 12:06
Sample (adjusted): 5/13/2014 6/23/2016
Included observations: 528 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIBR(-1)	-0.846345	0.043121	-19.62720	0.0000
C	0.050366	0.034948	1.441181	0.1501
@TREND("5/12/2014")	-1.29E-05	0.000114	-0.112967	0.9101

R-squared	0.423221	Mean dependent var	0.000243
Adjusted R-squared	0.421024	S.D. dependent var	0.525570
S.E. of regression	0.399909	Akaike info criterion	1.010506
Sum squared resid	83.96177	Schwarz criterion	1.034762
Log likelihood	-263.7736	Hannan-Quinn criter.	1.020002
F-statistic	192.6138	Durbin-Watson stat	2.026963
Prob(F-statistic)	0.000000		

Table A6: Phillips-Perron Unit Root Test results on the order imbalance series,

Regime 3.

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

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-19.77439	0.0000
Test critical values:	1% level	-3.975532	
	5% level	-3.418354	
	10% level	-3.131670	

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

Residual variance (no correction)	0.159018
HAC corrected variance (Bartlett kernel)	0.173010

Phillips-Perron Test Equation
Dependent Variable: D(OIBR)
Method: Least Squares
Date: 01/29/17 Time: 15:29
Sample (adjusted): 5/13/2014 6/23/2016
Included observations: 528 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIBR(-1)	-0.846345	0.043121	-19.62720	0.0000
C	0.050366	0.034948	1.441181	0.1501
@TREND("5/12/2014")	-1.29E-05	0.000114	-0.112967	0.9101

R-squared	0.423221	Mean dependent var	0.000243
Adjusted R-squared	0.421024	S.D. dependent var	0.525570
S.E. of regression	0.399909	Akaike info criterion	1.010506
Sum squared resid	83.96177	Schwarz criterion	1.034762
Log likelihood	-263.7736	Hannan-Quinn criter.	1.020002
F-statistic	192.6138	Durbin-Watson stat	2.026963
Prob(F-statistic)	0.000000		

Table A7: Correlogram of daily order imbalance, Regime 1.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.048	0.048	0.2911	0.590
		2	0.067	0.065	0.8602	0.650
		3	0.035	0.030	1.0220	0.796
		4	0.166	0.160	4.6029	0.331
		5	0.053	0.037	4.9787	0.418
		6	-0.055	-0.082	5.3856	0.495
		7	-0.095	-0.109	6.5846	0.473
		8	-0.109	-0.130	8.1770	0.416
		9	0.067	0.079	8.7815	0.458
		10	-0.092	-0.056	9.9434	0.445
		11	-0.037	0.009	10.136	0.518
		12	-0.077	-0.028	10.960	0.532
		13	0.066	0.055	11.571	0.563
		14	-0.023	-0.027	11.649	0.634
		15	-0.175	-0.195	16.047	0.379
		16	0.061	0.089	16.577	0.413
		17	-0.042	-0.044	16.832	0.466
		18	-0.001	-0.021	16.833	0.535
		19	0.043	0.126	17.111	0.582
		20	-0.040	-0.066	17.348	0.630
		21	-0.046	-0.048	17.667	0.670
		22	-0.019	-0.070	17.721	0.722
		23	0.062	0.033	18.308	0.741
		24	-0.093	-0.058	19.651	0.716
		25	-0.002	-0.017	19.652	0.765
		26	-0.080	-0.035	20.682	0.758
		27	0.059	0.045	21.240	0.775
		28	-0.051	-0.033	21.659	0.797
		29	0.056	0.052	22.181	0.813
		30	-0.102	-0.137	23.926	0.775
		31	0.066	0.109	24.668	0.782
		32	-0.017	-0.104	24.720	0.817
		33	0.020	0.035	24.787	0.847
		34	-0.073	-0.039	25.703	0.846
		35	-0.049	-0.079	26.127	0.861
		36	-0.004	-0.025	26.130	0.887

Table A8: Correlogram of daily order imbalance, Regime 2.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.019	-0.019	0.1741	0.677
		2	-0.016	-0.017	0.2986	0.861
		3	-0.016	-0.017	0.4211	0.936
		4	-0.039	-0.040	1.1355	0.889
		5	-0.092	-0.095	5.1058	0.403
		6	0.035	0.029	5.6685	0.461
		7	-0.014	-0.018	5.7631	0.568
		8	-0.007	-0.012	5.7861	0.671
		9	0.053	0.046	7.1218	0.624
		10	0.041	0.037	7.9138	0.637
		11	0.022	0.030	8.1421	0.701
		12	-0.021	-0.022	8.3568	0.757
		13	0.025	0.030	8.6449	0.799
		14	0.006	0.020	8.6617	0.852
		15	-0.017	-0.011	8.7963	0.888
		16	-0.051	-0.049	10.028	0.865
		17	-0.060	-0.066	11.784	0.813
		18	-0.009	-0.008	11.820	0.856
		19	0.048	0.039	12.940	0.842
		20	0.068	0.058	15.199	0.765
		21	0.033	0.026	15.716	0.785
		22	0.105	0.103	21.067	0.517
		23	-0.047	-0.037	22.166	0.510
		24	-0.018	-0.007	22.325	0.560
		25	0.003	0.020	22.329	0.617
		26	-0.049	-0.033	23.528	0.603
		27	-0.044	-0.026	24.482	0.603
		28	0.002	-0.020	24.484	0.656
		29	-0.041	-0.051	25.313	0.662
		30	0.028	0.019	25.707	0.690
		31	0.078	0.057	28.713	0.584
		32	0.039	0.035	29.489	0.594
		33	0.027	0.024	29.853	0.625
		34	0.008	0.009	29.885	0.670
		35	0.054	0.072	31.320	0.646
		36	-0.059	-0.029	33.059	0.609

Table A9: Correlogram of daily order imbalance, Regime 3.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.154	0.154	12.564	0.000
		2	0.110	0.088	18.970	0.000
		3	0.064	0.036	21.170	0.000
		4	-0.040	-0.066	22.042	0.000
		5	-0.003	0.002	22.047	0.001
		6	0.007	0.016	22.073	0.001
		7	0.024	0.028	22.378	0.002
		8	0.022	0.011	22.651	0.004
		9	0.002	-0.010	22.653	0.007
		10	0.055	0.053	24.297	0.007
		11	0.073	0.063	27.195	0.004
		12	-0.015	-0.043	27.324	0.007
		13	0.064	0.054	29.527	0.006
		14	-0.014	-0.028	29.628	0.009
		15	0.024	0.031	29.940	0.012
		16	-0.025	-0.040	30.282	0.017
		17	-0.026	-0.018	30.654	0.022
		18	0.017	0.021	30.810	0.030
		19	0.049	0.057	32.149	0.030
		20	-0.002	-0.025	32.151	0.042
		21	0.016	-0.004	32.293	0.055
		22	-0.038	-0.045	33.101	0.060
		23	-0.005	0.015	33.112	0.079
		24	0.036	0.038	33.827	0.088
		25	-0.087	-0.097	38.069	0.046
		26	0.020	0.026	38.286	0.057
		27	-0.071	-0.057	41.098	0.040
		28	-0.042	-0.017	42.099	0.042
		29	-0.017	-0.012	42.266	0.053
		30	-0.038	-0.027	43.075	0.058
		31	-0.061	-0.054	45.174	0.048
		32	-0.055	-0.036	46.865	0.044
		33	-0.041	-0.009	47.818	0.046
		34	0.021	0.032	48.076	0.055
		35	0.030	0.044	48.590	0.063
		36	-0.030	-0.040	49.088	0.072

8 APPENDIX II

Table A10: Augmented Dickey-Fuller Unit Root Test results on the imbalance coefficient series.

Null Hypothesis: COEFF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.908022	0.0011
Test critical values:	1% level	-4.144584	
	5% level	-3.498692	
	10% level	-3.178578	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(COEFF)
Method: Least Squares
Date: 01/05/17 Time: 14:54
Sample (adjusted): 2 53
Included observations: 52 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COEFF(-1)	-0.646428	0.131709	-4.908022	0.0000
C	0.003425	0.002127	1.610613	0.1137
@TREND("1")	1.46E-06	6.74E-05	0.021610	0.9828

R-squared	0.330096	Mean dependent var	0.000224
Adjusted R-squared	0.302753	S.D. dependent var	0.008723
S.E. of regression	0.007284	Akaike info criterion	-6.950257
Sum squared resid	0.002600	Schwarz criterion	-6.837685
Log likelihood	183.7067	Hannan-Quinn criter.	-6.907100
F-statistic	12.07238	Durbin-Watson stat	1.941439
Prob(F-statistic)	0.000055		

Table A11: Phillips-Perron Unit Root Test results on the imbalance coefficient series.

Null Hypothesis: COEFF has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.924528	0.0011
Test critical values:	1% level	-4.144584	
	5% level	-3.498692	
	10% level	-3.178578	

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

Residual variance (no correction)	5.00E-05
HAC corrected variance (Bartlett kernel)	5.09E-05

Phillips-Perron Test Equation
Dependent Variable: D(COEFF)
Method: Least Squares
Date: 01/29/17 Time: 15:18
Sample (adjusted): 2 53
Included observations: 52 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COEFF(-1)	-0.646428	0.131709	-4.908022	0.0000
C	0.003425	0.002127	1.610613	0.1137
@TREND("1")	1.46E-06	6.74E-05	0.021610	0.9828

R-squared	0.330096	Mean dependent var	0.000224
Adjusted R-squared	0.302753	S.D. dependent var	0.008723
S.E. of regression	0.007284	Akaike info criterion	-6.950257
Sum squared resid	0.002600	Schwarz criterion	-6.837685
Log likelihood	183.7067	Hannan-Quinn criter.	-6.907100
F-statistic	12.07238	Durbin-Watson stat	1.941439
Prob(F-statistic)	0.000055		

Table A12: Augmented Dickey-Fuller Unit Root Test results on the aggregate turnover series.

Null Hypothesis: TURNOVER has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.882982	0.1763
Test critical values:	1% level	-4.144584	
	5% level	-3.498692	
	10% level	-3.178578	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TURNOVER)
Method: Least Squares
Date: 01/05/17 Time: 15:02
Sample (adjusted): 2 53
Included observations: 52 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TURNOVER(-1)	-0.346824	0.120300	-2.882982	0.0058
C	1836068.	722993.7	2.539535	0.0143
@TREND("1")	11332.84	8505.421	1.332426	0.1889

R-squared	0.154734	Mean dependent var	64832.47
Adjusted R-squared	0.120234	S.D. dependent var	964345.1
S.E. of regression	904515.8	Akaike info criterion	30.32415
Sum squared resid	4.01E+13	Schwarz criterion	30.43672
Log likelihood	-785.4279	Hannan-Quinn criter.	30.36731
F-statistic	4.484968	Durbin-Watson stat	2.173616
Prob(F-statistic)	0.016268		

Table A13: Phillips-Perron Unit Root Test results on the aggregate turnover series.

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

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.747347	0.2229
Test critical values:	1% level	-4.144584	
	5% level	-3.498692	
	10% level	-3.178578	

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

Residual variance (no correction)	7.71E+11
HAC corrected variance (Bartlett kernel)	7.07E+11

Phillips-Perron Test Equation
Dependent Variable: D(TURNOVER)
Method: Least Squares
Date: 01/29/17 Time: 15:20
Sample (adjusted): 2 53
Included observations: 52 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TURNOVER(-1)	-0.346824	0.120300	-2.882982	0.0058
C	1836068.	722993.7	2.539535	0.0143
@TREND("1")	11332.84	8505.421	1.332426	0.1889

R-squared	0.154734	Mean dependent var	64832.47
Adjusted R-squared	0.120234	S.D. dependent var	964345.1
S.E. of regression	904515.8	Akaike info criterion	30.32415
Sum squared resid	4.01E+13	Schwarz criterion	30.43672
Log likelihood	-785.4279	Hannan-Quinn criter.	30.36731
F-statistic	4.484968	Durbin-Watson stat	2.173616
Prob(F-statistic)	0.016268		

Table A14: Augmented Dickey-Fuller Unit Root Test results on the first difference in aggregate turnover series.

Null Hypothesis: D(TURNOVER) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.736456	0.0001
Test critical values:	1% level	-4.161144	
	5% level	-3.506374	
	10% level	-3.183002	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TURNOVER,2)
Method: Least Squares
Date: 01/05/17 Time: 15:08
Sample (adjusted): 6 53
Included observations: 48 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TURNOVER(-1))	-2.298521	0.400687	-5.736456	0.0000
D(TURNOVER(-1),2)	0.890224	0.341233	2.608843	0.0125
D(TURNOVER(-2),2)	0.564130	0.249179	2.263955	0.0288
D(TURNOVER(-3),2)	0.421794	0.142539	2.959154	0.0051
C	-392414.6	286871.4	-1.367911	0.1786
@TREND("1")	17180.47	9191.512	1.869167	0.0686

R-squared	0.742873	Mean dependent var	19456.49
Adjusted R-squared	0.712263	S.D. dependent var	1584661.
S.E. of regression	850029.6	Akaike info criterion	30.26040
Sum squared resid	3.03E+13	Schwarz criterion	30.49430
Log likelihood	-720.2496	Hannan-Quinn criter.	30.34879
F-statistic	24.26874	Durbin-Watson stat	2.057277
Prob(F-statistic)	0.000000		

Table A15: Phillips-Perron Unit Root Test results on the first difference in aggregate turnover series.

Null Hypothesis: D(TURNOVER) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-12.40086	0.0000
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

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

Residual variance (no correction)	8.08E+11
HAC corrected variance (Bartlett kernel)	3.18E+11

Phillips-Perron Test Equation
Dependent Variable: D(TURNOVER,2)
Method: Least Squares
Date: 01/29/17 Time: 15:21
Sample (adjusted): 3 53
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TURNOVER(-1))	-1.344479	0.136770	-9.830250	0.0000
C	-182794.2	271201.8	-0.674015	0.5035
@TREND("1")	9482.489	8833.523	1.073466	0.2884

R-squared	0.668476	Mean dependent var	16213.14
Adjusted R-squared	0.654662	S.D. dependent var	1576295.
S.E. of regression	926316.9	Akaike info criterion	30.37284
Sum squared resid	4.12E+13	Schwarz criterion	30.48648
Log likelihood	-771.5075	Hannan-Quinn criter.	30.41627
F-statistic	48.39292	Durbin-Watson stat	2.120421
Prob(F-statistic)	0.000000		

Table A16: Granger causality test results of market liquidity (proxied by the first difference in aggregate turnover) and market inefficiency (proxied by order imbalance coefficient in monthly regression of daily returns on order imbalances), Entire Sample.

Pairwise Granger Causality Tests
Date: 01/05/17 Time: 16:12
Sample: 1 52
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
D_TURNOVER_ does not Granger Cause COEFF	46	1.08033	0.3942
COEFF does not Granger Cause D_TURNOVER_		0.19765	0.9752

Table A17: Granger causality test results of market liquidity (proxied by the first difference in aggregate turnover) and market inefficiency (proxied by order imbalance coefficient in monthly regression of daily returns on order imbalances), Regime 1.

Pairwise Granger Causality Tests
Date: 01/05/17 Time: 16:16
Sample: 1 5
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
D_TURNOVER_ does not Granger Cause COEFF	4	0.30135	0.6804
COEFF does not Granger Cause D_TURNOVER_		1913.90	0.0145

Table A18: Granger causality test results of market liquidity (proxied by the first difference in aggregate turnover) and market inefficiency (proxied by order imbalance coefficient in monthly regression of daily returns on order imbalances), Regime 2.

Pairwise Granger Causality Tests
Date: 01/05/17 Time: 16:18
Sample: 1 20
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
D_TURNOVER_ does not Granger Cause COEFF	14	0.43863	0.8182
COEFF does not Granger Cause D_TURNOVER_		0.99145	0.6460

Table A19: Granger causality test results of market liquidity (proxied by the first difference in aggregate turnover) and market inefficiency (proxied by order imbalance coefficient in monthly regression of daily returns on order imbalances), Regime 3.

Pairwise Granger Causality Tests
Date: 01/05/17 Time: 16:20
Sample: 1 25
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
D_TURNOVER_ does not Granger Cause COEFF	19	1.00242	0.4989
COEFF does not Granger Cause D_TURNOVER_		0.36596	0.8767

9 APPENDIX III

Table A20: Augmented Dickey-Fuller Unit Root Test results on the daily return series, Regime 1.

Null Hypothesis: AVG_LN_RETURN_ has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.48875	0.0000
Test critical values:	1% level	-4.031309	
	5% level	-3.445308	
	10% level	-3.147545	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(AVG_LN_RETURN_)
Method: Least Squares
Date: 01/14/17 Time: 12:17
Sample (adjusted): 1/04/2012 6/29/2012
Included observations: 128 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_LN_RETURN_(-1)	-1.350922	0.128797	-10.48875	0.0000
D(AVG_LN_RETURN_(-...	0.252003	0.089342	2.820658	0.0056
C	0.002512	0.001326	1.894966	0.0604
@TREND("1/02/2012")	-2.50E-05	1.75E-05	-1.427623	0.1559

R-squared	0.565607	Mean dependent var	8.33E-05
Adjusted R-squared	0.555097	S.D. dependent var	0.010863
S.E. of regression	0.007246	Akaike info criterion	-6.985989
Sum squared resid	0.006511	Schwarz criterion	-6.896863
Log likelihood	451.1033	Hannan-Quinn criter.	-6.949777
F-statistic	53.81851	Durbin-Watson stat	2.020278
Prob(F-statistic)	0.000000		

Table A21: Phillips-Perron Unit Root Test results on the daily return series, Regime 1.

Null Hypothesis: AVG_LN_RETURN_ has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-12.23638	0.0000
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

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

Residual variance (no correction)	5.37E-05
HAC corrected variance (Bartlett kernel)	4.36E-05

Phillips-Perron Test Equation
Dependent Variable: D(AVG_LN_RETURN_)
Method: Least Squares
Date: 01/29/17 Time: 16:50
Sample (adjusted): 1/03/2012 6/29/2012
Included observations: 129 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_LN_RETURN_(-1)	-1.083870	0.089586	-12.09862	0.0000
C	0.001985	0.001325	1.497250	0.1368
@TREND("1/02/2012")	-2.00E-05	1.76E-05	-1.131425	0.2600

R-squared	0.537469	Mean dependent var	8.27E-05
Adjusted R-squared	0.530128	S.D. dependent var	0.010821
S.E. of regression	0.007417	Akaike info criterion	-6.946997
Sum squared resid	0.006932	Schwarz criterion	-6.880490
Log likelihood	451.0813	Hannan-Quinn criter.	-6.919974
F-statistic	73.20720	Durbin-Watson stat	2.026538
Prob(F-statistic)	0.000000		

Table A22: Augmented Dickey-Fuller Unit Root Test results on the daily return series, Regime 2.

Null Hypothesis: AVG_LN_RETURN_ has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.71487	0.0000
Test critical values:	1% level	-3.977131	
	5% level	-3.419133	
	10% level	-3.132131	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(AVG_LN_RETURN_)
Method: Least Squares
Date: 01/14/17 Time: 12:22
Sample (adjusted): 7/03/2012 5/09/2014
Included observations: 484 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_LN_RETURN_(-1)	-1.035228	0.045575	-22.71487	0.0000
C	0.001109	0.000715	1.551335	0.1215
@TREND("7/02/2012")	-2.20E-06	2.55E-06	-0.862551	0.3888

R-squared	0.517537	Mean dependent var	-6.52E-06
Adjusted R-squared	0.515531	S.D. dependent var	0.011252
S.E. of regression	0.007832	Akaike info criterion	-6.855052
Sum squared resid	0.029504	Schwarz criterion	-6.829130
Log likelihood	1661.923	Hannan-Quinn criter.	-6.844866
F-statistic	257.9837	Durbin-Watson stat	1.997709
Prob(F-statistic)	0.000000		

Table A23: Phillips-Perron Unit Root Test results on the daily return series, Regime 2.

Null Hypothesis: AVG_LN_RETURN_ has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-22.85166	0.0000
Test critical values:	1% level	-3.977131	
	5% level	-3.419133	
	10% level	-3.132131	

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

Residual variance (no correction)	6.10E-05
HAC corrected variance (Bartlett kernel)	5.17E-05

Phillips-Perron Test Equation
Dependent Variable: D(AVG_LN_RETURN_)
Method: Least Squares
Date: 01/29/17 Time: 16:58
Sample (adjusted): 7/03/2012 5/09/2014
Included observations: 484 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_LN_RETURN_(-1)	-1.035228	0.045575	-22.71487	0.0000
C	0.001109	0.000715	1.551335	0.1215
@TREND("7/02/2012")	-2.20E-06	2.55E-06	-0.862551	0.3888

R-squared	0.517537	Mean dependent var	-6.52E-06
Adjusted R-squared	0.515531	S.D. dependent var	0.011252
S.E. of regression	0.007832	Akaike info criterion	-6.855052
Sum squared resid	0.029504	Schwarz criterion	-6.829130
Log likelihood	1661.923	Hannan-Quinn criter.	-6.844866
F-statistic	257.9837	Durbin-Watson stat	1.997709
Prob(F-statistic)	0.000000		

Table A24: Augmented Dickey-Fuller Unit Root Test results on the daily return series, Regime 3.

Null Hypothesis: AVG_LN_RETURN_ has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-23.27877	0.0000
Test critical values:	1% level	-3.974707	
	5% level	-3.417952	
	10% level	-3.131432	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(AVG_LN_RETURN_)
Method: Least Squares
Date: 01/14/17 Time: 12:27
Sample (adjusted): 5/13/2014 6/24/2016
Included observations: 554 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_LN_RETURN_(-1)	-1.003692	0.043116	-23.27877	0.0000
C	0.000258	0.000937	0.275377	0.7831
@TREND("5/12/2014")	-7.25E-07	2.93E-06	-0.247671	0.8045

R-squared	0.495870	Mean dependent var	-7.19E-05
Adjusted R-squared	0.494041	S.D. dependent var	0.015489
S.E. of regression	0.011017	Akaike info criterion	-6.173334
Sum squared resid	0.066879	Schwarz criterion	-6.149956
Log likelihood	1713.013	Hannan-Quinn criter.	-6.164201
F-statistic	270.9864	Durbin-Watson stat	1.977065
Prob(F-statistic)	0.000000		

Table A25: Phillips-Perron Unit Root Test results on the daily return series, Regime 3.

Null Hypothesis: AVG_LN_RETURN_ has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-23.32643	0.0000
Test critical values:	1% level	-3.974707	
	5% level	-3.417952	
	10% level	-3.131432	

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

Residual variance (no correction)	0.000121
HAC corrected variance (Bartlett kernel)	0.000101

Phillips-Perron Test Equation
Dependent Variable: D(AVG_LN_RETURN_)
Method: Least Squares
Date: 01/29/17 Time: 17:02
Sample (adjusted): 5/13/2014 6/24/2016
Included observations: 554 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_LN_RETURN_(-1)	-1.003692	0.043116	-23.27877	0.0000
C	0.000258	0.000937	0.275377	0.7831
@TREND("5/12/2014")	-7.25E-07	2.93E-06	-0.247671	0.8045

R-squared	0.495870	Mean dependent var	-7.19E-05
Adjusted R-squared	0.494041	S.D. dependent var	0.015489
S.E. of regression	0.011017	Akaike info criterion	-6.173334
Sum squared resid	0.066879	Schwarz criterion	-6.149956
Log likelihood	1713.013	Hannan-Quinn criter.	-6.164201
F-statistic	270.9864	Durbin-Watson stat	1.977065
Prob(F-statistic)	0.000000		

Table A26: Correlogram of daily returns, Regime 1.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.072	-0.072	0.6844	0.408
		2	-0.223	-0.230	7.3733	0.025
		3	-0.018	-0.057	7.4152	0.060
		4	0.196	0.146	12.638	0.013
		5	-0.068	-0.057	13.275	0.021
		6	-0.198	-0.150	18.716	0.005
		7	0.043	0.000	18.977	0.008
		8	0.070	-0.025	19.664	0.012
		9	0.112	0.146	21.433	0.011
		10	-0.022	0.066	21.503	0.018
		11	0.002	0.028	21.503	0.029
		12	-0.009	-0.026	21.515	0.043
		13	0.083	0.066	22.513	0.048
		14	-0.163	-0.156	26.421	0.023
		15	-0.176	-0.159	31.019	0.009
		16	0.061	-0.017	31.578	0.011
		17	0.111	0.025	33.456	0.010
		18	-0.047	-0.007	33.795	0.013
		19	-0.031	0.042	33.947	0.019
		20	0.036	-0.063	34.147	0.025
		21	0.005	-0.063	34.150	0.035
		22	-0.117	-0.117	36.316	0.028
		23	-0.054	-0.038	36.783	0.034
		24	0.096	0.104	38.277	0.032
		25	-0.019	0.016	38.336	0.043
		26	0.005	0.044	38.339	0.056
		27	0.030	0.037	38.491	0.070
		28	0.063	0.003	39.155	0.078
		29	0.086	0.088	40.418	0.077
		30	0.011	0.061	40.438	0.097
		31	-0.122	-0.057	43.015	0.074
		32	-0.027	-0.003	43.145	0.090
		33	0.054	-0.008	43.665	0.101
		34	0.005	-0.014	43.669	0.124
		35	0.022	0.078	43.760	0.147
		36	0.047	0.024	44.156	0.165

Table A27: Correlogram of daily returns, Regime 2.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.034	-0.034	0.5573	0.455
		2	-0.014	-0.015	0.6565	0.720
		3	0.041	0.040	1.4880	0.685
		4	-0.123	-0.121	8.9271	0.063
		5	-0.070	-0.078	11.329	0.045
		6	0.003	-0.007	11.333	0.079
		7	0.117	0.127	18.115	0.011
		8	-0.021	-0.022	18.332	0.019
		9	0.083	0.069	21.785	0.010
		10	-0.067	-0.082	24.036	0.008
		11	-0.028	0.001	24.430	0.011
		12	-0.015	-0.014	24.540	0.017
		13	0.054	0.081	25.983	0.017
		14	-0.089	-0.114	29.919	0.008
		15	0.014	0.006	30.018	0.012
		16	0.083	0.050	33.497	0.006
		17	-0.021	0.034	33.718	0.009
		18	-0.027	-0.054	34.075	0.012
		19	-0.092	-0.102	38.343	0.005
		20	-0.034	-0.049	38.926	0.007
		21	-0.045	-0.005	39.944	0.008
		22	0.041	0.028	40.788	0.009
		23	-0.009	-0.029	40.830	0.012
		24	-0.012	-0.053	40.899	0.017
		25	0.033	0.015	41.467	0.020
		26	-0.074	-0.040	44.300	0.014
		27	-0.060	-0.037	46.132	0.012
		28	-0.035	-0.056	46.776	0.014
		29	-0.011	-0.036	46.834	0.019
		30	-0.044	-0.042	47.854	0.020
		31	0.012	-0.003	47.929	0.027
		32	0.079	0.067	51.151	0.017
		33	-0.021	-0.028	51.387	0.022
		34	0.031	0.020	51.898	0.025
		35	0.013	0.025	51.986	0.032
		36	-0.016	0.025	52.116	0.040

Table A28: Correlogram of daily returns, Regime 3.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.004	-0.004	0.0073	0.932
		2	-0.086	-0.086	4.0958	0.129
		3	0.027	0.026	4.4959	0.213
		4	-0.047	-0.054	5.7091	0.222
		5	-0.015	-0.011	5.8337	0.323
		6	0.033	0.023	6.4380	0.376
		7	-0.033	-0.033	7.0684	0.422
		8	-0.046	-0.044	8.2824	0.406
		9	-0.001	-0.009	8.2826	0.506
		10	0.034	0.031	8.9343	0.538
		11	0.002	0.001	8.9376	0.628
		12	-0.003	-0.003	8.9421	0.708
		13	-0.007	-0.009	8.9730	0.775
		14	-0.035	-0.032	9.6738	0.786
		15	0.009	0.006	9.7225	0.837
		16	-0.050	-0.061	11.152	0.800
		17	-0.023	-0.020	11.450	0.832
		18	-0.021	-0.032	11.696	0.863
		19	0.086	0.087	15.945	0.661
		20	-0.006	-0.015	15.964	0.719
		21	-0.003	0.006	15.970	0.771
		22	0.012	0.003	16.049	0.813
		23	0.046	0.055	17.295	0.795
		24	-0.055	-0.057	19.058	0.749
		25	0.061	0.062	21.223	0.680
		26	0.050	0.046	22.677	0.651
		27	-0.069	-0.044	25.435	0.550
		28	-0.009	-0.008	25.483	0.601
		29	0.022	0.007	25.756	0.639
		30	-0.058	-0.050	27.709	0.586
		31	0.031	0.028	28.269	0.607
		32	0.008	-0.010	28.309	0.654
		33	0.036	0.059	29.071	0.663
		34	-0.069	-0.082	31.904	0.571
		35	-0.120	-0.112	40.499	0.241
		36	-0.022	-0.038	40.798	0.268

Table A29: Augmented Dickey-Fuller Unit Root Test results on the squared daily return series, Regime 1.

Null Hypothesis: SQ_RETURN has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.35250	0.0000
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SQ_RETURN)
Method: Least Squares
Date: 01/14/17 Time: 12:20
Sample (adjusted): 1/03/2012 6/29/2012
Included observations: 129 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SQ_RETURN(-1)	-1.011488	0.089098	-11.35250	0.0000
C	3.09E-05	1.44E-05	2.152478	0.0333
@TREND("1/02/2012")	3.80E-07	1.91E-07	1.983650	0.0495

R-squared	0.505648	Mean dependent var	8.82E-07
Adjusted R-squared	0.497801	S.D. dependent var	0.000112
S.E. of regression	7.97E-05	Akaike info criterion	-16.01331
Sum squared resid	8.01E-07	Schwarz criterion	-15.94680
Log likelihood	1035.858	Hannan-Quinn criter.	-15.98628
F-statistic	64.43962	Durbin-Watson stat	1.999066
Prob(F-statistic)	0.000000		

Table A30: Phillips-Perron Unit Root Test results on the squared daily return series, Regime 1.

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

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-11.36164	0.0000
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

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

Residual variance (no correction)	6.21E-09
HAC corrected variance (Bartlett kernel)	5.72E-09

Phillips-Perron Test Equation
Dependent Variable: D(SQ_RETURN)
Method: Least Squares
Date: 01/29/17 Time: 16:51
Sample (adjusted): 1/03/2012 6/29/2012
Included observations: 129 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SQ_RETURN(-1)	-1.011488	0.089098	-11.35250	0.0000
C	3.09E-05	1.44E-05	2.152478	0.0333
@TREND("1/02/2012")	3.80E-07	1.91E-07	1.983650	0.0495

R-squared	0.505648	Mean dependent var	8.82E-07
Adjusted R-squared	0.497801	S.D. dependent var	0.000112
S.E. of regression	7.97E-05	Akaike info criterion	-16.01331
Sum squared resid	8.01E-07	Schwarz criterion	-15.94680
Log likelihood	1035.858	Hannan-Quinn criter.	-15.98628
F-statistic	64.43962	Durbin-Watson stat	1.999066
Prob(F-statistic)	0.000000		

Table A31: Augmented Dickey-Fuller Unit Root Test results on the squared daily return series, Regime 2.

Null Hypothesis: SQ_RETURNS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 8 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.492654	0.0413
Test critical values:	1% level	-3.977454	
	5% level	-3.419290	
	10% level	-3.132224	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SQ_RETURNS)
Method: Least Squares
Date: 01/14/17 Time: 12:24
Sample (adjusted): 7/13/2012 5/09/2014
Included observations: 476 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SQ_RETURNS(-1)	-0.310409	0.088875	-3.492654	0.0005
D(SQ_RETURNS(-1))	-0.709482	0.091453	-7.757895	0.0000
D(SQ_RETURNS(-2))	-0.616871	0.094202	-6.548364	0.0000
D(SQ_RETURNS(-3))	-0.519037	0.092036	-5.639498	0.0000
D(SQ_RETURNS(-4))	-0.463420	0.086504	-5.357214	0.0000
D(SQ_RETURNS(-5))	-0.531499	0.081416	-6.528192	0.0000
D(SQ_RETURNS(-6))	-0.430480	0.075690	-5.687410	0.0000
D(SQ_RETURNS(-7))	-0.194618	0.065213	-2.984340	0.0030
D(SQ_RETURNS(-8))	-0.190121	0.045580	-4.171123	0.0000
C	1.76E-05	1.09E-05	1.610313	0.1080
@TREND("7/02/2012")	6.05E-09	3.62E-08	0.166991	0.8674

R-squared	0.561043	Mean dependent var	-1.14E-07
Adjusted R-squared	0.551603	S.D. dependent var	0.000160
S.E. of regression	0.000107	Akaike info criterion	-15.42186
Sum squared resid	5.34E-06	Schwarz criterion	-15.32560
Log likelihood	3681.403	Hannan-Quinn criter.	-15.38401
F-statistic	59.43291	Durbin-Watson stat	2.016153
Prob(F-statistic)	0.000000		

Table A32: Phillips-Perron Unit Root Test results on the squared daily return series, Regime 2.

Null Hypothesis: SQ_RETURNS has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-22.92818	0.0000
Test critical values:	1% level	-3.977131	
	5% level	-3.419133	
	10% level	-3.132131	

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

Residual variance (no correction)	1.33E-08
HAC corrected variance (Bartlett kernel)	3.01E-08

Phillips-Perron Test Equation
Dependent Variable: D(SQ_RETURNS)
Method: Least Squares
Date: 01/29/17 Time: 17:00
Sample (adjusted): 7/03/2012 5/09/2014
Included observations: 484 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SQ_RETURNS(-1)	-0.939591	0.045520	-20.64134	0.0000
C	4.50E-05	1.08E-05	4.180758	0.0000
@TREND("7/02/2012")	5.24E-08	3.78E-08	1.385788	0.1665

R-squared	0.469722	Mean dependent var	2.06E-08
Adjusted R-squared	0.467517	S.D. dependent var	0.000159
S.E. of regression	0.000116	Akaike info criterion	-15.28163
Sum squared resid	6.46E-06	Schwarz criterion	-15.25571
Log likelihood	3701.154	Hannan-Quinn criter.	-15.27144
F-statistic	213.0354	Durbin-Watson stat	2.018656
Prob(F-statistic)	0.000000		

Table A33: Augmented Dickey-Fuller Unit Root Test results on the squared daily return series, Regime 3.

Null Hypothesis: SQ_RETURNS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.95060	0.0000
Test critical values:	1% level	-3.974737	
	5% level	-3.417967	
	10% level	-3.131441	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SQ_RETURNS)
Method: Least Squares
Date: 01/14/17 Time: 12:29
Sample (adjusted): 5/14/2014 6/24/2016
Included observations: 553 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SQ_RETURNS(-1)	-0.737961	0.056983	-12.95060	0.0000
D(SQ_RETURNS(-1))	-0.132614	0.043979	-3.015369	0.0027
C	3.27E-05	1.93E-05	1.692475	0.0911
@TREND("5/12/2014")	2.06E-07	6.13E-08	3.365764	0.0008

R-squared	0.416885	Mean dependent var	2.87E-06
Adjusted R-squared	0.413698	S.D. dependent var	0.000292
S.E. of regression	0.000224	Akaike info criterion	-13.96422
Sum squared resid	2.75E-05	Schwarz criterion	-13.93301
Log likelihood	3865.108	Hannan-Quinn criter.	-13.95203
F-statistic	130.8317	Durbin-Watson stat	1.928328
Prob(F-statistic)	0.000000		

Table A34: Phillips-Perron Unit Root Test results on the squared daily return series, Regime 3.

Null Hypothesis: SQ_RETURNS has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-20.72886	0.0000
Test critical values:	1% level	-3.974707	
	5% level	-3.417952	
	10% level	-3.131432	

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

Residual variance (no correction)	5.05E-08
HAC corrected variance (Bartlett kernel)	7.44E-08

Phillips-Perron Test Equation
Dependent Variable: D(SQ_RETURNS)
Method: Least Squares
Date: 01/29/17 Time: 17:03
Sample (adjusted): 5/13/2014 6/24/2016
Included observations: 554 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SQ_RETURNS(-1)	-0.849274	0.043665	-19.44962	0.0000
C	3.78E-05	1.93E-05	1.961697	0.0503
@TREND("5/12/2014")	2.35E-07	6.08E-08	3.860584	0.0001

R-squared	0.407197	Mean dependent var	2.87E-06
Adjusted R-squared	0.405045	S.D. dependent var	0.000292
S.E. of regression	0.000225	Akaike info criterion	-13.95319
Sum squared resid	2.80E-05	Schwarz criterion	-13.92981
Log likelihood	3868.034	Hannan-Quinn criter.	-13.94406
F-statistic	189.2410	Durbin-Watson stat	1.965066
Prob(F-statistic)	0.000000		

Table A35: Correlogram of squared daily returns, Regime 1.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.019	0.019	0.0488	0.825
		2	0.039	0.039	0.2561	0.880
		3	-0.095	-0.096	1.4645	0.690
		4	0.035	0.037	1.6290	0.804
		5	-0.011	-0.005	1.6450	0.896
		6	0.063	0.052	2.1963	0.901
		7	0.059	0.064	2.6741	0.913
		8	0.024	0.015	2.7584	0.949
		9	-0.115	-0.111	4.6284	0.865
		10	-0.100	-0.093	6.0704	0.809
		11	0.014	0.027	6.0977	0.867
		12	-0.032	-0.050	6.2511	0.903
		13	0.054	0.041	6.6820	0.918
		14	-0.009	-0.003	6.6935	0.946
		15	0.080	0.079	7.6466	0.937
		16	-0.009	0.024	7.6598	0.958
		17	-0.086	-0.089	8.7873	0.947
		18	-0.036	-0.028	8.9907	0.960
		19	0.053	0.035	9.4255	0.966
		20	-0.154	-0.185	13.132	0.872
		21	0.174	0.181	17.897	0.655
		22	0.040	0.052	18.153	0.697
		23	-0.084	-0.140	19.290	0.684
		24	-0.033	0.057	19.467	0.727
		25	-0.112	-0.105	21.508	0.664
		26	0.143	0.132	24.883	0.526
		27	0.035	0.036	25.090	0.569
		28	0.065	0.003	25.808	0.584
		29	-0.023	-0.021	25.899	0.631
		30	0.045	0.057	26.251	0.662
		31	0.007	0.079	26.260	0.709
		32	0.078	0.043	27.314	0.703
		33	0.030	0.035	27.474	0.739
		34	0.143	0.085	31.117	0.610
		35	0.045	0.075	31.489	0.638
		36	-0.067	-0.067	32.299	0.645

Table A36: Correlogram of squared daily returns, Regime 2.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.065	0.065	2.0525	0.152
		2	0.175	0.172	17.074	0.000
		3	0.178	0.163	32.626	0.000
		4	0.138	0.100	42.011	0.000
		5	0.041	-0.023	42.840	0.000
		6	0.185	0.127	59.737	0.000
		7	0.287	0.262	100.33	0.000
		8	0.059	-0.001	102.08	0.000
		9	0.285	0.188	142.30	0.000
		10	0.139	0.042	151.87	0.000
		11	0.136	0.040	161.05	0.000
		12	0.060	-0.032	162.86	0.000
		13	0.219	0.093	186.80	0.000
		14	0.010	-0.092	186.84	0.000
		15	0.140	0.040	196.68	0.000
		16	0.105	-0.057	202.22	0.000
		17	0.087	-0.001	206.05	0.000
		18	0.097	-0.004	210.81	0.000
		19	0.089	-0.006	214.86	0.000
		20	0.059	-0.065	216.61	0.000
		21	0.034	0.008	217.20	0.000
		22	0.112	-0.007	223.58	0.000
		23	0.036	0.022	224.23	0.000
		24	0.140	0.078	234.24	0.000
		25	0.022	-0.030	234.49	0.000
		26	0.083	0.003	238.01	0.000
		27	0.046	0.035	239.11	0.000
		28	0.070	0.008	241.68	0.000
		29	0.052	0.035	243.07	0.000
		30	0.015	-0.047	243.19	0.000
		31	0.145	0.087	254.14	0.000
		32	0.005	-0.021	254.15	0.000
		33	0.023	-0.065	254.42	0.000
		34	0.070	0.027	257.02	0.000
		35	0.087	0.047	261.04	0.000
		36	0.015	-0.006	261.16	0.000

Table A37: Correlogram of squared daily returns, Regime 3.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.167	0.167	15.612	0.000
		2	0.170	0.146	31.697	0.000
		3	0.074	0.027	34.772	0.000
		4	0.095	0.059	39.798	0.000
		5	0.114	0.082	47.055	0.000
		6	0.119	0.073	55.009	0.000
		7	0.185	0.136	74.379	0.000
		8	0.119	0.047	82.369	0.000
		9	0.180	0.112	100.77	0.000
		10	0.016	-0.068	100.91	0.000
		11	0.115	0.058	108.38	0.000
		12	0.104	0.053	114.50	0.000
		13	0.015	-0.074	114.64	0.000
		14	0.044	-0.020	115.72	0.000
		15	0.093	0.058	120.72	0.000
		16	0.079	0.005	124.28	0.000
		17	0.039	-0.015	125.15	0.000
		18	0.076	0.025	128.46	0.000
		19	0.151	0.132	141.53	0.000
		20	0.133	0.067	151.76	0.000
		21	0.024	-0.059	152.08	0.000
		22	0.069	0.041	154.86	0.000
		23	0.038	-0.016	155.69	0.000
		24	0.053	-0.011	157.35	0.000
		25	0.066	0.028	159.87	0.000
		26	0.043	-0.032	160.95	0.000
		27	0.072	-0.004	164.00	0.000
		28	0.040	-0.012	164.95	0.000
		29	0.099	0.075	170.76	0.000
		30	0.036	-0.005	171.53	0.000
		31	0.136	0.069	182.42	0.000
		32	0.033	0.005	183.09	0.000
		33	0.043	0.009	184.19	0.000
		34	0.068	0.013	186.91	0.000
		35	0.033	-0.014	187.56	0.000
		36	-0.021	-0.089	187.81	0.000