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JSE Equity Market Liquidity: The Impact of Technology and Resultant Microstructure Changes

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ABSTRACT

The JSE Equity Market has evolved significantly since floor trading ended in 1996. Fast and efficient trading technology is attractive to market participants based not only locally but internationally as well. How quick and cost effectively a trader can enter and exit a market plays a significant role in defining a market place's liquidity.

Liquidity is multidimensional, making it not only difficult to isolate a particular dimension but also challenging to fully measure, according to Liu (2006). Growth in trading activity following each trading engine upgrade in the JSE Equity Market has been quite evident. The microstructure changes, such as low latency trading that came about because of the technological enhancement and the plethora of academic research concerning high speed trading and liquidity, begged the question as to whether there was a trend regarding the exchange's liquidity. It also questioned whether all liquidity was the same and whether it truly was as multidimensional as some authors have suggested.

The purpose of this study was, using different liquidity measurements and methodologies, to determine whether liquidity improved or diminished during an eight-year period from 2 July 2005 to 1 July 2013. An ANOVA analysis was done using each liquidity measurement's results to determine differentiation between each July-to-July year and ascertain whether the liquidity was affected particularly after the implementation of the JSE's latest trading engine upgrade. The study also aimed to determine whether these liquidity measurements liquidity rankings were in any way connected to each other using correlation. Thirdly, a portfolio event study was conducted to gauge whether the impact on liquidity due to the JSE's 2012 trading engine upgrade, was statistically significant. Lastly, the aforementioned liquidity measurements which had shown changes in liquidity that were statistically significant were compared to the activity of low latency trading strategies on the JSE. Overall, the results were varied and not fully conclusive to show a positive relationship between the trading engine upgrade, low latency trading and liquidity.

DECLARATION

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1 INTRODUCTION

The JSE Equity Market has evolved significantly since floor trading ended in 1996 with technological trading system enhancements that have arguably been one of the key forces in transforming the exchange into the premier exchange in Africa. Today, the JSE is the 19th largest exchange in the world, based on market capitalisation according to the World Federation of Exchanges (WFE 2013). Fast and efficient trading technology is attractive to market participants based not only locally but internationally as well. How quick and cost effectively a trader can enter and exit a market, plays a significant role in defining a market place's liquidity.

Liquidity is multidimensional, making it not only difficult to isolate a particular dimension but also challenging to fully measure, according to Liu (2006).

There are numerous elements which contribute towards a market's liquidity and its efficiency. The challenge for many exchanges is to provide a market place that offers market participants the ability to execute large quantities of stock at a low enough cost that can result in minimal price impact. Quick, easy and cost effective access and exit of a market remains the quintessential goal for the majority of market participants. Apart from trading costs, frictions such as demand pressure, inventory risk and the access to private information all contribute towards the illiquidity of a market place. The JSE Equity Market liquidity is no exception as all these aforementioned frictions impact the exchange's marketability as a preferred market place.

Trading that happens in microseconds as opposed to milliseconds has redefined automated trading and ultimately low latency trading, worldwide. The JSE recognised the need to remain attractive to this sector of the market especially considering that up to 56% of equity trades in the US and 38% of equity trades in Europe are of a high frequency trading (HFT) nature (Tabb, 2010). Hence the need to introduce trading solution technology to the market place that was relevant to the global exchange world and that would foster speedy executions.

The new trading platform Millennium Exchange^{TM}, developed by technology solutions provider MillenniumIT, was implemented on 2 July 2012. The new technology has allowed market participants to execute in the JSE Equity Market central order book at speeds almost 400 times faster than the previous trading engine, JSE TradElect, originally housed in London as of 2007 (Corporate Communications Consultants, 2011). The vision behind the implementation of the more advanced technology would not only bring a low latency advantage to market participants and attract HFT activity (thereby encouraging trading volumes), but the relocation of the trading solution from London to Johannesburg would further enhance operational stability (Corporate Communications Consultants, 2011). The significant reliance that the JSE and market participants once placed on the UK-SA connectivity links when the trading engine was housed abroad was therefore no longer pertinent.

In order to remain relevant within the international capital market space, exchanges must offer sufficient liquidity. Cumming, Johan and Li (2011) support this as they mention that an exchange's primary role is to provide liquidity. It can therefore be argued that because of regulatory progressions and technological advancements such as the development of highly complex trading technology, the emergence of multiple trading venues seen internationally and the subsequent introduction of algorithmic trading (AT) and HFT, the importance of offering liquidity has grown exponentially. Montalvo (2003) states that an exchange's success is ultimately associated with the level of liquidity it employs.

Having said that, it is necessary to truly understand why liquidity is important in the capital market space. Muranaga (1999) highlights this by stating that market liquidity significantly impacts price discovery in the market and is therefore thought to have a close relationship with market efficiency and stability as well. Sarr and Lybek (2002) agree with this notion by stating that certain markets are attractive because of improved allocation and information efficiency. Central to these benefits is liquidity and whether large quantities can be sold without impacting its market price. Sarr and Lybek (2002) continue that liquid assets are categorised by small transaction costs, easy trading, timely settlement and by having minimal effect on market prices. These are all attractive attributes to market players around the world who are no longer restricted because of geographical challenges, have the freedom to search for trading venues that are accessible and that offer the best possible profit opportunities.

When examining annualised JSE Equity Market liquidity levels in Table 1 that follows, it is evident that liquidity figures are relatively low when compared to international exchange houses such as the London Stock Exchange, Deutsche Boerse and Shanghai Stock Exchange which have liquidity levels between 70% and 155% (WFE 2013).

Table 1: Annualised JSE Equity Market Liquidity (2005 - 2012)

2012	2011	2010	2009	2008	2007	2006	2005
43%	50%	48%	52%	83%	58%	48%	40%

Source: JSE (2013)

What is of interest is that although JSE Equity Market liquidity appears to have decreased over the last number of years, the general trading activity on the exchange has grown significantly. One could argue that the JSE's Equity Market liquidity levels have fluctuated over the past several years due to factors which include global sentiment, technological advancements, changes in market microstructure, the demand for South African securities and due to developments in both local and international regulatory frameworks. However, it could also be argued that different liquidity measurements could show different results.

Many of the characteristics of market liquidity can be dealt with using traditional liquidity measures, such as bid-ask spreads, turnover ratios and selected price-based indicators. Sarr and Lybek (2002), however, highlight that these indicators are not conclusive and possess the danger of sending mixed signals particularly during times of uncertainty and crisis. The authors suggest that these indicators cannot be viewed in isolation and should be seen in context with numerous market specific factors which affect asset and market liquidity.

The purpose of this study was, using different liquidity measurements and methodologies, to determine whether liquidity improved or diminished during an eight-year period from 2 July 2005 to 1 July 2013. An ANOVA analysis was done using each liquidity measurement's results to determine differentiation between each July-to-July year and ascertain whether the liquidity was affected particularly after the implementation of the JSE's latest trading engine upgrade. The study also aimed to determine whether these liquidity measurements liquidity rankings were in any way connected to each other using correlation. Thirdly, a portfolio event study was conducted to gauge whether the impact on liquidity due to the JSE's 2012 trading engine upgrade, was statistically significant. Lastly, the aforementioned liquidity measurements which had shown changes in liquidity that were statistically significant were compared to the activity of low latency trading strategies on the JSE

The study is structured as follows. Following this opening section, Chapter 2 offers a detailed overview of the literature that forms the contextual framework of this study. Chapters 3 and 4 unpack the complexity of market liquidity in terms of the factors that typically affect it and the strengths and weaknesses of certain liquidity measures. Next, Chapter 5 looks at how technological advancements and the market microstructure changes that resulted because of these advancements have impacted liquidity. Chapter 6 explains the data and methodologies applied. Penultimately, Chapter 7 offers insights into the analysis and results of the data presented in this research. Lastly, Chapter 8 offers concluding remarks.

2 LITERATURE REVIEW

In trying to define liquidity, an article by Liu (2006, p.1) mentions that “liquidity is generally described as the ability to trade large quantities quickly at low cost with little price impact”. The author also states that existing liquidity measurements only really examine a single dimension of liquidity, when liquidity is actually multidimensional. Therefore Liu (2006) believes that existing measures only really reveal a partial ability to encapsulate liquidity risk and could possibly be imprecise even in the dimension the measurement strives to isolate.

In support of Liu’s (2006) statement that liquidity is multidimensional, a key study by authors Amihud, Mendelson and Pedersen (2005) emphasises that liquidity is a complex concept and that a number of illiquidity sources exist. These sources or frictions that lead to illiquidity, according to the authors, include exogenous transaction costs, demand pressure and inventory risk, private information and locating a counterparty with specific criteria in mind, such as a particular security or a particular quantity of that security. This study emphasises the numerous factors that affect liquidity, which is vital in cementing an understanding of the intricacies of liquidity. Another article by Chordia, Roll and Subrahmanyan (2002) considers the numerous explanatory variables used to influence liquidity as their study examines the aggregated market spreads, depths, volume and number of daily transactions for US stocks. Although it is difficult to compare the South African context to the US market, the study offers valuable command of the subject matter that is liquidity.

An interesting view from Wuyts (2007) analyses the economic forces that determine and foster liquidity within stock markets and the many dimensions of liquidity. The author also examines whether liquidity is a desirable feature seeing as there are two schools of thought: a “dark” view and a “bright” view (Wuyts 2007, p. 281). The dark view refers to the hazards of liquidity where liquid markets are now generally focused on the short term and on investors who are no longer concerned with fundamentals when choosing companies and formulating their investment decisions (Wuyts, 2007). The author states that uncertainty is the end result which ultimately impacts financial systems holistically. The bright view believes that investors are more likely to engage in the market when liquidity is at its optimum (Wuyts 2007). The result is that in increasing the number of participants in the market, the price impact of trades is restricted and ultimately fosters a stable market (Wuyts, 2007).

A very significant supposition is that of Sarr and Lybek (2002) who suggest that liquidity measurements cannot be viewed on their own and should instead be seen in context with numerous market specific factors. The authors offer an overview of indicators that can indeed be utilised to demonstrate and analyse liquidity developments in financial markets. In particular, the authors focus on the different aspects of market liquidity which are applied in certain foreign exchange, money and capital markets so as to indicate their effective practicality.

Amihud (2002, p.1) adds that although "finer measures of illiquidity", such as the bid-ask spreads mentioned in Chapter 1, are possible to calculate, the liquidity measures themselves make it impossible to measure the long-term series of illiquidity that is required to test the effects over time of liquidity. Instead, the author's illiquidity ratio (ILLIQ), which is the daily ratio of absolute stock return to its dollar (in this case, Rand) volume, averaged over a year, is indeed able to do so. This measurement plays a particularly central role in the data analysis to follow in Chapter 6.

However, a contrasting article by Goyenko, Holden and Trzcinka (2009) suggests an alternative measure to the widely used ILLIQ measurement. These authors believe that there is little evidence or agreement on which liquidity measures are more effective and whether these measurements consider the transaction costs of market participants.

Following the unpacking of liquidity and understanding some of the many factors that impact it, Grossman and Miller (1988) present a basic model representing market structure that encapsulates the essence of market liquidity. In addition, Handa and Schwarts (1996) offer a brief introduction to the different market structures and the effect on liquidity provision.

Technological improvements to an exchange's infrastructure are key in facilitating a liquid and efficient market. When discussing the impact of technology and market structure on liquidity, an article by Jain (2003) offers insights into the trading mechanism and structural features of 51 stock exchanges and the effect of these characteristics on closing bid-ask spreads, volatility and trading turnover.

A relevant study by Amihud, Mendelson and Lauterbach (1997) examines the value of an improvement in the market structure of certain stocks on the Tel Aviv Stock Exchange. The authors explore the value discovery, trading efficiency and stock liquidity following the transition from a once-a-day call auction to repeated continuous trading after an opening daily call auction session. Although this research is not focused on a technological upgrade per se, but rather a market structure change, it still offers insight into how improving the quality of a trading mechanism can improve market liquidity and the implications of a market structure change.

Although technology is a key driver in the evolution of trading and liquidity, regulatory changes have proven to be the catalyst in shaping trading strategies. In particular, the introduction of the Regulation National Market System (RegNMS) allowed for increased competition within the US equity market because multiple trading venues started to appear (Deutsche Bank Research, 2011). As a result, technological enhancements lead to the birth of HFT, a microstructure change, as traders sought to gain rapid access to multiple trading platforms to exploit arbitrage opportunities (Deutsche Bank Research, 2011). Menkveld (2011) therefore focuses on fragmentation which resulted in the arrival of HFT – essentially a multi-venue market maker due to the fact that its operation uses capital to produce liquidity. Although HFT is not explicitly focused on in this study, the aforementioned studies are necessary in order to formulate a foundation to understand low latency trading and its effects on liquidity.

Brogaard (2010) differentiates between AT and HFT and finds that although similar, HFT is defined by traders holding positions for very short periods of time with the intention to end the day neutral, whereas AT involves the traders holding their positions for much longer periods. With that being said, Hendershott, Jones and Menkveld (2011) examine whether the increased AT improves market liquidity and whether it should be encouraged. In their research, the authors found that the spreads of large NYSE stocks narrowed and both adverse selection and trade-related price discovery reduced due to AT. In support of this, Hendershott and Riordan (2012) add that AT demands liquidity when bid-ask spreads are narrow and provides liquidity when spreads are wide.

3 STOCK MARKET LIQUIDITY

Providing a market that offers timely, cost effective and efficient execution services is vital, more so now than ever before. In a world where multiple trading venues exist, where latency arbitrage is the overriding investment strategy and where "the race to zero"[1] is more heightened than before, exchanges cannot afford to be left behind. As Montalvo (2003) states, an exchange's success is ultimately associated with the level of liquidity it employs.

The JSE Equity Market consists of a number of trading segments which classify or segment securities based on varying degrees of liquidity and with that, also harbour varying degrees of liquidity risk:

a) ZA01: Top 40 companies and the most liquid shares traded on the JSE Equity Market;
b) ZA02: Medium liquid companies;
c) ZA03: Less liquid companies which include AltX companies.

These three segments consist of predominantly ordinary shares.

There are multiple reasons as to why certain shares are more liquid than others. Liu (2006) believes that in fact it is firms themselves who could cause illiquidity. Should a firm hold a high probability of default or show poor management style, investors would shy away from their distressed stocks and they would naturally become less liquid (Liu, 2006).

It would be imprudent to think that the number of factors that affect liquidity could be short listed and that they operate in isolation. Instead, these factors are often all deeply intertwined and interconnected with each other. Factors such as the large market capitalisation of companies, whether they are dual listed on other international exchanges (which allow for arbitrage) and their availability of free float stock for secondary trading, have arguably made the Top 40 stocks the most liquid on the JSE Equity Market. ZA02 and ZA03 consist of medium and small sized market capitalisation companies, respectively, such as AltX companies, where their available free float stock for secondary trading is generally low.

From a regulatory perspective, the JSE's Listing Requirements stipulate the required level of free float stock for the Main Board and AltX companies. AltX firms have lower free float

[1] Refers to the notion of zero latency and the challenge that technology providers face in achieving little to no latency within their systems.

stock requirements than Main Board companies. Typically, a large proportion of AltX firms' stock is held by these companies' directors, business founders and staff, leaving low levels of freely tradable stock for the market. This is a complex cycle – market participants do not trade these stocks as they are not particularly liquid and these stocks are not liquid because they are not particularly traded.

There are however two particular opinions or sides to liquidity. A significant consideration is that of Wuyts (2007) who refers to the dark side of liquidity with reference to the dangers of liquidity as he cites Keynes (1935) who viewed liquidity as a cause of undermining or unhinging markets, a notion that appears seemingly counterintuitive. The reasoning behind this is that liquid markets are generally focused largely on the short term and investors have moved away from fundamentals when choosing companies and formulating their investment decisions (Wuyts, 2007). Contrary to this, the bright view emphasises the significance and the advantages of liquidity for a spectrum of market participants (Wuyts, 2007). According to the author, investors are more likely to engage in the market when liquidity is at its optimum. Thus, increasing the number of participants in the market restricts the price impact of trades and ultimately fosters a stable market (Wuyts, 2007).

There are a number of beneficial effects of increased liquidity for various market participants who support the bright view (Wuyts, 2007), such as that:

a) traders reap the reward from increased liquidity as it facilitates purchases and sales of securities at lower costs which ultimately impacts their portfolio strategy;
b) the author cites Pastor and Stambough (2003) who state that liquidity is perceived to be a risk factor priced into the market and therefore liquidity can be seen as risk-reducing as investors would be more open to holding assets that offer greater liquidity;
c) that liquidity remains vital for stock exchanges' competitiveness and as an attractive investment platform;
d) liquidity influences decisions of firms regarding the cost of capital, as liquidity is viewed as determinant of asset returns.

Liu (2006) states that liquidity only truly becomes an important factor when the economy is expected to find itself in a recessionary state. In essence, this means that in such situations investors would naturally gravitate towards assets that are considered less risky and which can be easily and quickly bought or sold.

Although the benefits of liquidity are paramount, this does not rule out the possibility of global financial instability (Wuyts, 2007). Wuyts (2007, p.286) refers to the "commonality in liquidity", when different assets' liquidity move or shift together, as previously outlined by Chordia, Roll and Subrahmanyam (2001). Hasbrouck and Seppi (2001) also refer to the same belief. Contrary to this belief is O'Hara (2004) who states that overall, this movement in liquidity would not result in financial instability. O'Hara (2004, p.6) has two arguments for this. Firstly, that when investors leave one asset, they tend to stay in the market and opt for other asset types, thus localising "flight to quality" and not creating global exposure. Secondly, such commonality might just trigger investors to enter the market and thus because of the influx of participants, stability is ultimately improved and sustained.

Although liquidity is important, Amihud, Mendelson and Pedersen (2005) cite Grossman and Stiglitz (1980) who argue that there must be a certain degree of illiquidity in the market as well. Amihud, Mendelson and Pedersen (2005) support this notion by adding that an equilibrium level of illiquidity means that the market must be sufficiently liquid to compensate liquidity providers (suppliers) but not so illiquid that it becomes attractive to new liquidity suppliers to enter the market.

On the far end of the spectrum, too much illiquidity is not conducive to a functioning market either. Sarr and Lybek (2002) believe that illiquid markets reflect a symptom as opposed to a cause of inadequate market functioning. The authors argue that the only sustainable way to develop liquid financial markets is to ensure sound and transparent economic policies which are supported by suitable trading, clearing and settlement systems and prudent central bank intervention to manage systemic risk. Amihud, Mendelson and Pedersen (2005) suggest that illiquidity is the result of exogenous trading costs, private information, inventory risk and search challenges. These factors and others are discussed in section 3.1 to follow.

Overall, the greater the number of frictions that inhibit easy and speedy executions within the market, the less efficient the market appears. Therefore an inefficient market is an illiquid market.

3.1 Factors that Affect Stock Market Liquidity

Wuyts (2007) examines the numerous factors that affect stock market liquidity and the implications of these determinants. The author notes that a vital part in examining the performance of certain trading systems is its liquidity as liquidity determines traders' and other market agents' cost of buying or selling securities within the market. Apart from this, the author states that liquidity is also fundamental to exchanges to attract order flow from existing and potential traders. Wuyts (2007) adds that liquid markets entice order flow and liquidity and therefore also serve as a reason for firms to list themselves on the exchange as it is a factor in determining the firm's cost of capital.

The number of factors that affect liquidity is clearly significant, therefore only a few factors that are predominantly linked to trading, exchange and market structure, will be discussed in section 3.1.1 and onwards.

3.1.1 Transaction Costs

Amihud, Mendelson and Pedersen (2005) state that exogenous transaction costs such as brokerage fees, order processing costs and taxes impact the liquidity of a security. The more attractive the costs associated with transacting in a market, the easier investors will find it to recoup their return and the more willing investors would be to churn their stock (Amihud, Mendelson and Pedersen, 2005).

Amihud, Mendelson and Pedersen (2005) cite Amihud and Mendelson (1986) whose views are that a risk neutral investor, when buying a security and expecting to pay transaction costs when settling the trade, would take these trading costs and future transaction costs into account when valuing the security. This ultimately affects purchase and sale of the security, that is, its liquidity.

Transaction costs within the JSE Equity Market have always been a contentious point for market participants, for exactly the reasons mentioned by Amihud, Mendelson and Pedersen (2005) above. Understanding the importance of fostering a liquid and sustainable market, JSE Equity Market reviewed its trading fee methodology. As of 30 September 2013, all transactions are to be charged a trading fee based on value at 0.0053% with a cap of R300 (JSE Equity Market Price List v.02, 2013). This revision has meant that market participants have greater predictability and certainty around fees that they will be charged which is a contributing factor to liquidity. It would be telling to determine the effects of this change in billing methodology on liquidity and although this falls outside the scope of this particular study, it is a rich source of information for follow-up studies.

The impact of transaction costs extends to clientele effects (with respect to an investor's preferred stock holding period) and liquidity as well. Amihud, Mendelson and Pedersen

(2005) believe investors' desires to trade in any period or in their expected holding period is purely subjective. The authors argue that investors will only truly be moved to liquidate their stock when faced with the likelihood of a large enough liquidity shock or when the probability of the introduction of a lucrative investment opportunity is significant enough to force the investor to close out their current position in favour of the more lucrative option. It is therefore necessary for each market participant to understand its costs and required return. With this said, each investor views the impact of transaction costs on their required return differently. Amihud, Mendelson and Pedersen (2005) believe that a long-term investor who would be able to depreciate transaction costs over an extended expected holding period would require a lower required return versus a short-term investor who would require the opposite. The authors suggest that in equilibrium, liquid assets are held by short-term (frequently trading) investors whereas the illiquid stock is held by long-term investors.

3.1.2 Private Information

The cost of a transaction includes more than the explicit fee. Amihud, Mendelson and Pedersen (2005) believe that a transaction could still be costly if market participants have private information regarding the fundamentals of a particular stock or private information about order flow. The authors indicate that when participants have access to private information, a buyer of a security might be apprehensive that a potential seller has access to privileged information (for example the company operating at a loss), whilst the seller might be uneasy that the buyer has privileged information that the company is about to flourish. Therefore, the authors are of the view that trading with an informed market participant means that a loss will be incurred.

Regarding private information about order flow, Amihud, Mendelson and Pedersen (2005) state that if a trading desk is informed that a hedge fund needs to rid itself of a large position and that this liquidation will lower share prices, the trading desk could sell early at still high prices and repurchase the stock at lower prices. Similarly, Liu (2006) positions asymmetric information to influence liquidity and create illiquidity. A situation could occur where, should investors be privy to private information, uniformed investors could learn of this advantage and opt to not trade and consequently inhibit liquidity (Liu, 2006).

Informational efficiency is examined by the Chordia, Roll and Subrahmanyam (2001), who found that improved liquidity stimulates a higher level of informational efficiency as increased trading takes place using private information after a reduction in the tick size of a stock. However, Amihud, Mendelson and Pedersen (2005) refer to Grossman and Stiglitz (1980) who argue to dismiss informationally efficient markets. These authors believe that market prices cannot completely reflect all relevant and available information because if this was the case, no market participant would have the enticement to use resources to collect information from the start. Amihud, Mendelson and Pedersen (2005) reason that market participants who collect information must be compensated through investment performance that is significant. The authors also state that having differences in information across market participants is an equilibrium occurrence and therefore another source of illiquidity.

Bernstein (1987) believes that in order for a market to maintain the characteristics of a liquid market it depends on what motivates or incentivises buyers and sellers to enter the market right from the start. The author refers to two types of traders which ultimately help to shape the market into what it is. The first type is the noise trader who makes trades based on imperfect information and who will often force security prices away from its equilibrium price (Bernstein, 1987). Because of this shift, the result is undervaluation or overvaluation which appeals to information traders (the second type) who will push prices back to equilibrium levels (Bernstein, 1987). The authors therefore reveal that noise traders are a necessary part in maintaining a liquid market as they are vital for information traders to have someone to transact with them and that ultimately it is the noise trader who brings the depth, breadth and resiliency – and therefore liquidity. Bernstein (1987) concludes that the aforementioned characteristics encourage information traders to trade and that efficient prices can only occur if noise traders formulate inefficiencies through their constant purchases and sales.

3.1.3 Order Flows

Chordia, Roll and Subrahmanyam (2001) argue a slightly different position for liquidity. These authors ask whether liquidity is related to higher levels of arbitrageur activity and therefore a weakened connection between the prediction of future returns and past order flows – or rather an improved level of intraday market efficiency. The authors examine the predictability for NYSE stocks that traded on a daily basis over the period of 1993 to 2002. According to Chordia, Roll and Subrahmanyam (2001), short-horizon predictability of returns from past order flows had a negative relationship with efficiency and therefore also affected liquidity. As bid-ask spreads became narrower; it was evident that mid-quote return predictability decreased which suggests that outsiders were more active in taking on order flows during more liquid states of the market (Chordia, Roll and Subrahmanyam, 2001). The authors argue that short-horizon return predictability should be reduced by arbitrage trading, which, as is discussed in Chapter 5 dealing with HFT, should be more effective when the market is highly liquid.

The empirical results of the study show that intraday market efficiency is highly correlated to daily liquidity in that the forecast ability of stock returns from lagged order flows is meaningfully reduced on days when the market experiences heightened liquidity levels (Chordia, Roll and Subrahmanyam, 2001). Additionally, the authors' results indicate that efficiency is enhanced when the minimum tick size is further reduced which naturally means a reduction in spreads. When examining the time-of-day in terms of liquidity, it was found that during the mid-afternoon, liquidity was viewed at its optimum as order flow was less predictive of ensuing returns (Chordia, Roll and Subrahmanyam, 2001).

Overall, the authors find that liquidity plays an important role in creating efficiency as the return predictability from order flows is significantly reduced during periods of heightened liquidity levels.

3.1.4 Demand Pressure and Inventory Risk

According to Amihud, Mendelson and Pedersen (2005) demand pressure occurs because not all market participants are constantly present in the market and as a result if a market participant needs to liquidate their position, a buyer is not always instantly present. What transpires is that the seller may sell to a designated market maker who purchases stock in expectation of exiting their position at a later stage (Amihud, Mendelson and Pedersen, 2005). The authors conclude that because the market maker has taken on the risk of prices fluctuating constantly, the market maker needs to be compensated for this risk through ultimately imposing a cost on the seller, by setting a larger bid-ask spread which again ultimately affects liquidity.

3.1.5 Transparency

Transparency is seen as the ability of market participants to view information such as knowledge on prices before and after the trading process (Wuyts, 2007). The author states that transparency can have two extremes: one where more transparency is linked with more informative prices and the other extreme where transparency can diminish liquidity as traders might be reluctant to disclose their trading strategy. However, Wuyts (2007) adds that the effect of transparency is different for certain market participants, such as informed traders who prefer less transparency whereas liquidity traders (market makers) opt for more transparency or disclosure. Pagano and Roell (1996) also find that when more pre-trade transparency exists with bids, offers and depths, more liquidity is prevalent.

Wuyts (2007) also cites Rindi (2004) who establishes that, given a certain number of informed traders, liquidity would increase if markets' transparency improved. Wuyts (2007) adds, however, that if information becomes endogenous, for example if market participants pay for information to become better informed, the result is the opposite. The author explains that uninformed market participants might be unwilling to supply liquidity for large orders, as the origin of these orders might be information driven. The author continues by stating that informed traders do not have this issue and that when pre-trade transparency is heightened, market participants have less drive to become informed. In such a situation, Wuyts (2007) states that the number of informed traders diminish and this includes the liquidity that they provide.

3.1.6 Anonymity

Anonymity is linked to transparency in that informed traders would opt for anonymous trading whilst liquidity traders would not (Wuyts, 2007). The author references Benviste, Marcus and Wihelm (1992) who says that demand and supply anonymity differ. These authors argue that the reason for this is that concealing information about the identity of liquidity demanders widens the bid-ask spread (reducing liquidity) as suppliers of liquidity can discern between informed and uniformed traders.

3.1.7 Tick Size

Wuyts (2007) cites a number of empirical papers, namely Bacidore (1997), Ahn, Cao and Choe (1998), Griffiths et al. (1998), Goldstein and Kavjecz (2000) and Choridia and Ball (2001) that have researched the effect of tick sizes on market quality. Wuyts (2007) states that, generally speaking, these studies found that after a reduction in the tick size, the spread narrowed notably but the depth of the bid-ask decreased. Significant too is that as one dimension of liquidity improves, in this case the spread, another dimension (depth) actually weakens (Wuyts, 2007).

Theoretical models by Seppi (1997) and Parlour and Seppi (2001), cited by Jain (2003), indicate that tick sizes can change the dynamics of spreads that investors, within different institutional settings, face. Again Jain (2003) cites authors Bacidore (1997) and Chakravarty, Harris and Wood (2001) who considered the bid-ask spreads and tick sizes on the Toronto Exchange and NYSE and found that these spreads became significantly narrower as stocks' tick sizes became smaller.

3.1.8 Consolidation and Fragmentation of Markets

The Jain (2003) looks at consolidation and fragmentation of markets. The US market is particularly fragmented, through competition, which has a significant impact on liquidity. Jain (2003) cites Biais (1993) who believes that the mean spreads whether within a fragmented or consolidated market, are equal but more volatile in the latter. The consequences of fragmentation, from a microstructure perspective, are discussed further in Chapter 5.

3.1.9 Floor vs. Screen-Based Trading Systems

Jain (2003) states that gone are the halcyon days where exchanges would rely on dealer quotes or open-outcry trading. Instead, most if not all exchanges around the globe offer pure electronic limit order book trading now. Some exchanges such as NYSE Euronext (US) operate a "hybrid" trading system which comprises of electronic public order books but also open-outcry floor trading (Jain, 2003, p. 2).

The JSE's open outcry floor trading has not been in existence since 1996 and since then, all trading is electronic or on screen. A few exchanges still operate floor trading, although in conjunction with screen-based trading such as the NYSE Euronext (Wuyts, 2007). Biais, Foucault and Salanie (1998) suggest that floor trading (and in dealer markets) show wide spreads and inefficient risk sharing but that this is not the case in screen-based limit order markets. Interestingly, a study by Theissen (2002) who compares the floor and screen-based trading system of the Frankfurt Stock Exchange which at the time operated both of these platforms in parallel, finds that the screen-based trading system supplies narrower spreads for liquid stocks but that floor trading is more competitive for less liquid stocks.

Jain (2005) suggests that electronic trading has highly beneficial effects in the long run and that the equity premium has lowered meaningfully since moving from floor trading to electronic trading. Costs are greatly reduced when markets transition from a predominantly human interfaced market to machines and electronics – which for any cost sensitive market player becomes hugely appealing (Menkveld, 2011). The author supports this notion further by mentioning that market makers prefer to function in a market where transaction costs are low or access is immediate.

From a technological perspective, Menkveld (2011) highlights that a fast matching engine allows market making strategies to instantly update quotes as soon as public information has entered the market, which reduces the risk of adverse selection. At the same time, the low latency technology opens up the trading venue to a market making machine to “ping” the market and “test the waters” to gauge investor interest when the strategy tries to dispose of a costly inventory position (Menkveld, 2011).

Although it is beyond the scope of this study, it would be interesting to compare bid-ask spreads of the JSE during its floor trading days compared to its current screen-based trading system. Without doubt, the spreads would have narrowed considerably but it would be significant to see how this improvement in trading and information efficiency has helped to reduce spreads.

3.1.10 Limit Order Market vs. Dealer Market

Jain (2003) reiterates that the ultimate effectiveness of a stock exchange in performing its function of providing liquidity in listed securities can be significantly affected by institutional characteristics also known as exchange-design features.

The various trading mechanisms, such as a pure electronic limit order book, a dealer emphasis system and a hybrid mechanism of a periodic call mechanism, all provide liquidity on exchanges in varying degrees. Jain (2003) unpacks each type of trading mechanism:

a) Pure electronic limit order book: orders that enter the market are matched based on price and time priority – all unmatched orders are gathered within a consolidated order book for succeeding matching;
b) Dealer emphasis system: liquidity is supplied by brokers who quote bid and ask prices at which customers/market participants can trade with them. The downside of this mechanism is that customers’ orders could ultimately not enjoy the maximum level of exposure;
c) Hybrid mechanisms: these are defined as exchanges that utilise a combination of limit order book and dealer quotes by designated market makers;
d) Periodic call mechanism: Jain (2003, p.9) states that this mechanism is also known as the “price fixing mechanism” which gathers orders stretching over a particular period

and then finally does a batch process of these orders at a single price that would maximise volume.

Certain market mechanisms are more appealing to investors than others. Viswanathan and Wang (2002) highlight that risk-indifferent or risk-neutral investors prefer the limit order book structure, but that investors with an appetite for risk would prefer a dealer emphasis system. Glosten (1994) also states that the limit order book is the premium exchange structure as it offers the highest level of liquidity. In addition to these views, Jain (2003) cites Parlour and Seppi (2001) who believe that hybrid trading mechanisms can offer competition and operate and function alongside limit order book markets.

The study by Jain (2003) is important as it takes an in-depth look at whether the performance differences are actually found in the institutional differences across 51 international exchanges. Again, comparing trading costs on NYSE, a hybrid market and then on NASDAQ, a dealer market does not capture all the conceivable exchange designs, for example, using a pure limit order book (Jain, 2003). The author finds that the impact of individual institutional features such as the provision of automatic trade execution, order-flow transparency and fragmentation and the role of a market maker, make it very difficult to disentangle. This said, the study is successful in removing the gradual increased impact of each institutional feature on the ultimate performance of an exchange (Jain, 2003).

The main results of the study by Jain (2003) show that the institutional features of each exchange examined prove to be the key determinants of liquidity in its listed securities. The author controlled for firm-specific, market-specific and country-specific factors and found that the various exchanges' institutional traits had significant explanatory power in actually establishing the differences in the exchanges' liquidity performance. Specifically, Jain (2003) found that quoted spreads, effective spreads and volatility are at higher levels within dealer emphasis trading mechanisms than in pure electronic limit order book or hybrid mechanism trading systems. Within developed markets, hybrid mechanisms showed to have slightly lower average spreads than when examining pure electronic limit order book trading mechanisms (Jain, 2003). However, the author found the differences were quite significant within emerging markets. The author continues to assert that certain exchange features such as lower tick sizes, functioning market makers, a consolidated limit order book, automatic trade execution system and ante order-flow centralisation are all linked to lower bid-ask spreads.

In comparing limit order markets and dealer markets Wuyts (2007) supports Biais, Foucault and Salanie (1998) who find that theoretically the dealer market offers a large spread and inefficient risk sharing whereas limit order markets have more efficient prices. Pagano and Roell (1996) supports this as they find that an auction market charges reduced trading costs compared to a dealer market, which is consistent with the notion that the limit order book is more transparent compared to a dealer market.

Wuyts (2007) states that within a dealer market (quote driven market) there are three reasons for the existence of a spread, namely order handling and processing costs, inventory costs and asymmetric information. Within a limit order market, however, traders who are supplying liquidity can still be anticipated to need compensation for order handling costs but because no trader is obligated to make a market and take the opposite position to each trade leg, inventory risk is less likely to be of any significance (Wuyts, 2007).

A limit order market however, has no dealers or market makers whose responsibility and duty it is to offer liquidity (Wuyts, 2007). The author states that liquidity is only provided by traders and their unexecuted limit orders. Therefore, if the supply of limit orders dwindles it has a knock-on effect on trading. In addition, the author believes that all the dimensions of liquidity are established by the relationship between market orders which are demanding liquidity and limit orders which are supplying liquidity.

Glosten (1994) finds that a limit order market has a positive bid-ask spread due to the possibility of trading on private information. Handa, Schwarts and Tiwari (2003) also show that the width of the spread is determined by the difference in valuation amongst investors and because of adverse selection. Ultimately, the process of how information is reflected in stock prices through the facilitation of a limit order market is different from a quote driven or a hybrid system (Wuyts, 2007).

A study by Foucault, Kadan and Kandel (2005) shows that the resiliency of the limit order market heightens in proportion to patient traders and the waiting costs, but that it decreases with the order arrival rate. Foucault, Kadan and Kandel (2005) find through their model that during equilibrium, fewer patient traders are inclined to demand liquidity compared to more patient traders who are more likely to supply it. Also, the authors find that there is a positive relationship between the duration until a transaction occurs and the market resiliency. The authors suggest that the resiliency of the limit order book is always bigger when there is a minimum price variation (change) than when there is none.

The second liquidity dimension examined by Wuyts (2007) is that of prices and depth. The author cites Kavajecz and Odders-White (2001) who find that dealers modify their prices and depth in response to various events occurring in the market. The authors also find that depths are revised in response to transactions of any particular size but prices are only really modified when transaction sizes are greater than the quoted depth. In addition, these authors uncover that dealers respond more powerfully to alterations within the limit order book.

The JSE Equity Market is a limit order market and ultimately, within a limit order market, all the dimensions of liquidity including bid-ask spread, depth, immediacy and resiliency are established by the relationship and interaction between market orders demanding liquidity and limit orders, supplying liquidity (Wuyts, 2007).

3.1.11 Designated Market Makers

A designated market maker's duty and to a large degree, their obligation, is to supply bid and offer quotes and serve as the counterparty to incoming orders by managing and trading for their own book (Jain 2003).

Designated market makers are considered helpful in improving liquidity particularly when the market depth is not adequate and is devoid of synchronisation (Jain 2003). Some authors try to unpack how market makers function within the different trading mechanisms that exist, such as Glosten (1994), who foretells that limit order book markets are able to provide the greatest level of liquidity possible and that any competition brought on by other exchanges is either unprofitable or redundant. Jain (2003) explains that this means that market makers do not contribute liquidity above that offered by a pure electronic limit order book system. Glosten (1994) supports this by stating that no trader is worse off and that actually many traders are better off with an open limit order book structure than a system that allows monopolistic specialists. In the same vein, Jain (2003) cites Black (1995) who forecasts that with automated pure limit order books, dealers will not make profits and as a result, exchanges will not have market makers. An author that has a more negative view regarding market makers, cited by Jain (2003), is Rock (1989) who believes that market makers actually disrupt trading against pure limit order books and encourage second order adverse selection. Another view by Stoll (1998), also referred to by Jain (2003) is that by introducing competition across markets there is a reduction in the willingness of market makers to steady the markets and that electronic trading and technology also no longer make the role and importance of market makers sustainable even within dealer markets.

Relating this back to the JSE Equity Market, this market does not have a designated market maker programme, however it does require products such as exchange traded funds, exchange traded notes and warrants to be traded by market makers to ensure liquidity and price discovery.

3.2 Characteristics of Liquid Markets

Sarr and Lybek (2002) state that a liquid market exhibits five general characteristics:

a) Tightness: low transaction costs and low implicit costs;
b) Immediacy: the speed with which orders can be executed, cleared and settled;
c) Depth: the abundance of orders, which include actual and those easily found by buyers and sellers;
d) Breadth: orders are plentiful and large in volume with minimal impact on prices;
e) Resiliency: new orders flow quickly to correct order imbalances which result in prices moving away from its fundamental prices.

Wuyts (2007) emphasises that these characteristics or dimensions are interrelated and do not stand independently.

3.2.1 Tightness

The magnitude of transaction costs viewed as frictions can have a profound effect on a market's attractiveness and therefore its liquidity (Sarr and Lybek, 2002). The authors mention that high transaction costs ultimately destroy demand for trades and naturally reduce the number of potentially active investors in a market.

Moreover, the authors state that high transaction costs reduce the demand for trades and ultimately the number of market participants that could potentially participate actively in the market. Sarr and Lybek (2002) argue that the result of this is possible fragmentation as numerous transactions can occur within the market makers' spreads and not really around the equilibrium or fundamental price in the market. The authors conclude that the consequence is a shallow market.

However, when transaction costs are small, market participants opt to use dealers in auction driven markets rather than incur costs in searching for a counterparty (Sarr and Lybek, 2002). Transactions are then more likely to occur around the equilibrium price with the result being a market with more depth (Sarr and Lybek, 2002).

As mentioned above, high transaction costs mean that fewer market participants are willing to transact in the market. Therefore, fewer participants in the market mean that depth in the market diminishes (Sarr and Lybek, 2002). Similarly, the authors state that large transaction costs reduce resiliency because the elasticity of order flows decreases. This prevents orders from flowing quickly in order to correct order imbalances and influences prices away from the fundamental price (Sarr and Lybek, 2002).

It is important to note the theoretical foundation on which market liquidity is underpinned, namely the capital asset pricing model (CAPM) (Amihud, Mendelson and Pedersen, 2005). The authors refer to a particular assumption of CAPM where markets are frictionless (that is, perfectly liquid) where each instrument can be traded at zero cost constantly and that market participants accept the market price.

Amihud, Mendelson and Pedersen (2005) argue that alleviating frictions is expensive but that institutions, who attempted to alleviate these frictions, might be able to earn income. The authors explain that frictions include costs related to setting up markets, trading systems, legal cost and information and communication systems etc. The authors conclude that if frictions did not affect prices then these institutions that attempted to alleviate fictions would not be rewarded or compensated and as such, no one would have the motivation to alleviate these frictions. Based on these assumptions, markets cannot be frictionless.

3.2.2 Immediacy

In unpacking immediacy, Wuyts (2007) suggests that a particular reason why traders would prefer faster execution of orders is that slower execution speeds naturally increase the risk or uncertainty over the execution price. In fact, the author refers to Boehmer, Jennings and Wei (2006) who prove that markets seem to receive greater volumes of order flow if either the execution costs decline or the speed at which execution is done, has increased. Naturally, liquidity is affected. Conversely to this, Wuyts (2007) cites Boehmer (2005) who found a negative relationship between execution speed and costs when examining NASDAQ and NYSE stocks. Furthermore, the author found that execution is more costly on NASDAQ but also faster and that the difference in cost decreases monotonically with order size but that the difference in speed actually increases monotonically with order size.

3.2.3 Depth and Breadth

In the absence of breadth and depth, Sarr and Lybek (2002) highlight that due to a lack of continuous information that frequent market participants provide, the result could be discontinuities and uncertainty regarding equilibrium or fundamental prices.

Grossman and Stiglitz (1980) support this notion as the authors show that information asymmetries are vital to market equilibrium. They argue that if all information was contained in the security prices, no one would have the incentive to collate this information initially.

As the number of market participants decrease as a result of high transaction costs, so too is breadth and resiliency affected (Sarr and Lybek, 2002). The authors state that breadth suggests that there are a large number of market participants and therefore high trading fees result in shallow or thin markets. Again, the authors mention that as a knock-on effect, resiliency is reduced as orders are inhibited from flowing in quickly to stabilise any order imbalances that force prices into a state of disequilibrium.

Wuyts (2007) offers an example of where width and depth are dependent on immediacy. If a trader is patient and does not require an immediate trade, they could get more favourable prices and/or be in the position to trade a bigger amount at certain prices.

In examining volume-based measures, Sarr and Lybek (2002) state that these measures are ideal for measuring breadth which encompasses numerous and large orders in volume with little transaction price impact. According to the authors, markets that are deep are able to foster and encourage breadth as large orders can be broken up into much smaller orders and thus limit the impact on transaction prices. Hence, this suggests a favourable impact on liquidity.

3.2.4 Resiliency

Lastly, Wuyts (2007) unpacks resiliency which is defined as the speed with which market prices revert to original price levels following a change in prices. This results from a significant order flow disparity induced by uniformed traders (noise traders).

4 MEASURING LIQUIDITY

Sarr and Lybek (2002) cite (Baker 1996, p.1) who states that there is "no single unambiguous, theoretically correct or universally accepted definition of liquidity".

Significantly, liquidity can also be seen as a variety of liquidity types and the concept of liquidity as a whole is used to describe these different types (Sarr and Lybek, 2002). As alluded to previously, Liu (2006) believes that current liquidity measurements are only capable of examining a single dimension of liquidity, which is problematic when liquidity is deemed multidimensional. Amihud, Mendelson and Pedersen (2005) support this by reiterating that liquidity is a complex concept. Being mindful of this, it is clear that measuring liquidity requires using a number of proxies.

Sarr and Lybek (2002) differentiate between the varieties of liquidity as follows:

a) Asset liquidity refers to an asset that can be easily converted into legal tender with the key themes being transaction costs (or lack thereof) and immediacy;
b) An asset's market liquidity has a broader definition of asset liquidity in that it still entails the ease with which, given no new information, it is available to change an asset's fundamental price, big volumes of the asset can be quickly liquidated at a sensible price;
c) A financial market's liquidity is dependent on assets' substitutes and how liquid these appear to be; and
d) Lastly, institutional liquidity focuses on the ease with which financial institutions can transact with the objective of rapidly covering mismatches between their firm's assets and liabilities.

According to Sarr and Lybek (2002) an asset is deemed liquid if low transaction costs are involved, trading is seamless, settlement is timely and large value trades have little to no impact on the market price. The authors continue by stating that liquidity in itself and its characteristics is an evolving 'animal' that changes based on the stability of the environment.

Regarding the measurement of liquidity, Goyenko, Holden and Trzcinka (2009) argue that the measurements used to measure liquidity, or proxies of liquidity, do not accurately capture the characteristics of liquidity. The authors remark that numerous studies have suggested liquidity measures derived from daily return and volume data could serve as proxies for liquidity and transaction costs faced by investors. The authors add that a predominant assumption of a range of studies is that available liquidity proxies capture and reflect the transaction costs of market participants. The authors, however, do concede that this assumption has not been tested due to inadequate trading costs data. Goyenko, Holden and Trzcinka (2009) ultimately conclude that testing these liquidity proxies using actual trading data means that little agreement can be reached on which liquidity measures are better.

Because many studies use liquidity proxies using monthly or even more granular data, Goyenko, Holden and Trzcinka (2009) mention that there is a need for these proxies to be tested on a monthly basis. In addition, studies have suggested a variety of liquidity proxies which intend to reflect different liquidity benchmarks such as effective spread, realised spread or price impact (Goyenko, Holden and Trzcinka, 2009). The authors therefore conclude that because there are few liquidity proxies tested, few liquidity benchmarks and a lack of monthly proxies, it is not startling that there are conflicting views about which measure is better and whether these measures sufficiently capture the transaction costs.

4.1 Liquidity Measures

Sarr and Lybek (2002) state that liquidity measures can ultimately be classified into four different categories:

a) Transaction cost measures: encapsulate costs of trading and trading frictions within the secondary market;
b) Volume-based measures: breadth and depth of a market is measured;
c) Equilibrium price-based measures: attempt to capture orderly movements towards equilibrium prices i.e. resiliency;
d) Market-impact measures: examine the differences between price movements as a result of overall market conditions or the introduction of new information.

Again, Sarr and Lybek (2002) conclude that there is no single measure that clearly measures and reflects tightness, immediacy, breadth and resiliency.

4.1.1 Transaction Cost Measures

4.1.1.1 Bid-Ask Spread

Sarr and Lybek (2002) state that as a transaction cost measurement for liquidity, the bid-ask spread is the most all-encompassing measurement as it is able to not only capture explicit costs but implicit costs as well. It is therefore the most commonly used measure of transaction (execution) costs (Sarr and Lybek, 2002).

The calculation of the bid-ask spread as discussed by Sarr and Lybek (2002) entails using the highest bid and the lowest ask prices in the market for a particular time, or as is the norm in the market to use the latest figures. The authors caution that if there are many bid and ask prices from various market participants, it would be prudent to ignore the most extreme outliers.

Grossman and Miller (1988) discuss some of the limitations of the bid-ask spread as a measure of liquidity. The authors argue that this measure evaluates the market maker's return for supplying immediacy but only in the instance in which the market maker "crosses" the trade, that is, executes on the bid side and then on the offer or ask side. Thus, the spread is seen purely as a charge by the market maker for transacting orders, as opposed to supplying liquidity services meaning the bid-ask spread does not serve as a reliable measure (Grossman and Miller, 1988).

With their model in mind, Grossman and Miller (1988) state that orders do not arrive at the same time and that instead the orders are arbitrarily split over time. Therefore, because the price of a security may change constantly between the time at which the market maker buys and sells the security, realistically the market maker may reap much more or even much less than the spread quoted initially at the time of the buy or sell transaction (Grossman and Miller, 1988). Similarly to what the authors mentioned above, the currently quoted spread cannot assist any market participant in offering an accurate measure of the cost of trading immediately as opposed to delaying the order. Grossman and Miller (1988) state that the advantage of immediacy to a customer is the detaching of the price risk linked with waiting.

According to Jain (2003), certain features such as lower tick sizes, designated marker makers, a consolidated limit order book, automatic trade execution system and the centralisation of order flow, are all associated with lower bid-ask spreads.

4.1.2 Volume-Based Measures

Sarr and Lybek (2002) believe that volume-based measures, such as the turnover ratio and Amihud's Illiquidity Ratio, are the best at determining breadth in the market. The authors remark that deep markets mean that large orders can be broken up into smaller orders to reduce the impact it could have on transaction prices. The authors continue that a large number of trades are an ideal source of information not only to traders but dealers as well. These participants gather information about order flows and the imbalances in the order flow and then supply market participants with a sense of how accurate their quoted prices are (Sarr and Lybek, 2002).

4.1.2.1 Turnover Ratio

The turnover ratio examines the number of times the total number of shares of a particular company was traded compared to the total number of shares in issue for that company. The higher the turnover ratio; the greater the liquidity of that particular security.

According to Amihud and Mendelson (1986), the turnover ratio is in fact negatively related to illiquidity costs. In equilibrium, the more illiquid securities are allocated to investors with lower trading frequencies who repay the illiquidity cost over a longer period of time, thus alleviating the loss due to the asset's illiquidity costs (Amihud, 2002).

Sarr and Lybek (2002) believe that a drawback of the turnover ratio is that it can be particularly volatile as trading volume changes constantly not only during the day but also during the week and month.

4.1.2.2 Amihud's Illiquidity Ratio (ILLIQ)

Amihud and Mendelson (1986) states that the formation of Amihud's Illiquidity Ratio (ILLIQ) came about with the hypothesis that stock expected return is an increasing function of stock illiquidity.

The ratio is fairly easy to apply to data, truly a benefit when considering the numerous exchanges around the world and each exchange's varying level of available data (Amihud, 2002). ILLIQ is each stock's daily ratio of absolute stock return to its value traded and then averaged based on the number of trading days for each stock per year. Amihud (2002, p.32) explains it as being the "daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact". The author also highlights that this measurement is useful as it is easy to calculate. Daily stock data is generally available from most stock exchanges where in most markets microstructure data is very difficult to come by and because of time series data it is possible to examine the illiquidity-return relationship over an extended period of time (Amihud, 2002). The formula for ILLIQ is shown on the next page in Equation 1.

Equation 1: Amihud's Illiquidity Ratio (ILLIQ)

$$ILLIQ = |R_{iyt}|/VOLD_{iyt}$$

$|R_{iyt}|$ refers to the absolute return on stock i on day t of year y and $VOLD_{iyt}$ is the daily volume in Rands. After each year y, the illiquidity measure of stock t is averaged using the number of days for which stock i was traded in year y.

The ILLIQ measurement does have a particular advantage over other measurements, such as the Amivest measure. Amihud (2002) refers to this measure, which is very similar to the ILLIQ and cites Amihud, Mendelson and Lauterbach (1997) and Berkman and Elsewarapu (1998). These authors used this Amivest measure to determine the effect of changes in liquidity on the values of stocks that were prone to changes. The authors found that the measurement did not possess the instinctive interpretation of gauging the average daily link between one unit of volume and the stock's price change, as is the case with ILLIQ.

Zhang (2010) recognises that some liquidity measures actually require the use of high frequency transaction and quote data, which is not always readily available, particularly in emerging markets. Instead, the author mentions that several low frequency liquidity proxies exist and cites the following authors and their measurements, namely the Roll measure (Roll, 1984), Zeros measure (Lesmond, Ogden and Trzcinka, 1999), Amihud's illiquidity ratio (Amihud, 2002), the Gibbs measure (Hasbrouck, 2009) and Liu's LMx measure (Liu, 2006).

However, Zhang (2010) states that though the basic assumption is that the liquidity measures are capable of capturing actual liquidity, this has not been examined fully and the possibility exists that in using different liquidity measures to address the same issue, the results could be contradictory.

Another point to consider, although not part of the outcomes of this study, is that emerging markets could mean that liquidity is measured with more noise compared to liquidity that is measured in more established markets such as the US (Zhang, 2010). The author makes a point that typically within emerging markets, retail investors have much lower levels of disposable income to invest in the capital market and arguably have limited means to access information. Zhang (2010) therefore believes that these factors mean that emerging markets typically see low trading activity and therefore trading frequency plays a significant role especially within emerging markets. The aforementioned existing liquidity proxies hardly take this into account (Zhang, 2010).

Goyenko, Holden & Trzcinka (2009) highlight that whichever measure is used depends on what the researcher needs to measure. The authors state that the ILLIQ and Amivest measurements are not suitable proxies for measuring effective or realised spreads. Instead, Amihud's illiquidity ratio is applicable when wanting to measure price impact (Goyenko, Holden & Trzcinka, 2009).

Amihud (2002) also mentions, apart from the ILLIQ measure, measurements such as turnover ratio, market capitalisation and trading volume can all be seen as empirical proxies that evaluate different facets of illiquidity.

4.1.3 Price-Based Measures

4.1.3.1 Market-Efficiency Coefficient (MEC)

Hasbrouk and Schwartz (1988) suggest a market efficiency coefficient to discern between short-term and long-term price changes when new information enters the market.

The market-efficiency coefficient (MEC) observes that price changes are mostly uninterrupted in liquid market places even if new information is influencing equilibrium or fundamental prices (Sarr and Lybek, 2002). It is argued that given permanent price changes, the temporary changes to that price should be very slight in a resilient market (Sarr and Lybek, 2002). The authors explain that an MEC ratio of just below one indicates that the market is more resilient as only minimum amounts of short-term volatility are anticipated. They, however, continue to mention that instruments' prices that have low resiliency may also showcase more volatility and therefore more temporary changes during the periods in which their equilibrium price is changing. Sarr and Lybek (2002) indicate that factors that promote excessive short-term volatility include price rounding, spreads and inaccurate price discovery. The authors conclude that the result is that short-term period volatility is diminished relatively to longer-term volatility meaning that the MEC ratio moves above one.

Low levels of volatility are associated with orderly and resilient markets which offer much better price continuity – a desirable attribute of liquid markets (Sarr and Lybek, 2002).

The authors conclude that the MEC ratio determined over an extended period of time which covers notable discrete price changes could still be deemed an appropriate measure of resiliency. But, Sarr and Lybek (2002) mention that the measure may not be true for all types of markets with some detractors arguing that quote driven markets largely provide price continuity versus those markets that are order or call driven.

4.1.4 Market-Impact Measures

4.1.4.1 Market-Adjusted Liquidity

The market-adjusted liquidity measurement attempts to capture the price movement due to large volumes, that is, breadth (Sarr and Lybek, 2002).

Because of this, a regression model based on the capital asset pricing model (CAPM) is used to relate the residual of a regression of the security's return on the return of the market to ascertain the intrinsic liquidity of the security (Sarr and Lybek, 2002). The regression reveals that the lower the impact of trading volume on the changes of a security's price, the more liquid the asset is (Sarr and Lybek, 2002).

4.1.4.2 Price Impact

Breen, Hodrick and Korajczyk (2002) develop a measure of liquidity called price impact, which examines the magnitude with which a firm's share price changes when taking its traded volumes into account. The authors mention that price impact encapsulates the degree to which a transaction regarding a particular security affects that security's market price. Therefore, a very liquid asset will show very little price impact when traded, whereas illiquid securities cannot trade at any available price (Breen, Hodrick and Korajczyk, 2002). The authors argue that their measurement incorporates vital dimensions of liquidity which are not captured by the bid-ask spread and quoted depth.

The authors, however, find that the predicted price impact overstates the actual price impact for not only very large trades, but for trades that are executed more patiently and for trades where the institutional investors pay larger commissions.

5 TECHNOLOGY

The scope of this study is not only to examine the effect that the JSE trading engine upgrade has had on JSE Equity Market liquidity (with regard to ordinary shares), but also to understand how technological advancements have changed the exchange's micro market structure landscape and therefore its effect on liquidity trends. Technology has without a doubt transformed the way that electronic trading is done in the market.

Jain (2003) reiterates that factors such as rising globalisation, cross listings and even foreign portfolio investments have aggravated the levels of competition already evident between international exchanges. Apart from these factors, technology and its advancements have without a doubt turned the exchange world and the way it has always done business, on its head.

5.1 Evolution of Electronic Trading

The evolution of electronic trading has grown in leaps and bounds over the last 15 years. The technological advancements have to a degree been driven by a natural demand for greater and faster access to markets but were also driven by regulatory changes through the introduction of Regulation National Market System (Reg NMS) in the US and Markets in Financial Markets Directive (MiFID) within Europe. These legislative directives ultimately opened the capital markets up to increased competition for traditional exchanges through the establishment of Multilateral Trading Facilities (MTFs) and Electronic Crossing Networks (ECNs). With the increased competition, fragmentation increased and with that an increased desire to enter and exit each of these different trading venues as quickly and as lucratively as possible. Increased technological advancements also led to the birth of algorithmic trading and high frequency trading (HFT). Deutsche Bank Research (2011) shows that these two strategies differ, where the former is aimed at diminishing the negative impact of large institutional orders and high frequency traders (HFTs) opt to hold short-term positions but do not carry these positions over to the next trading day.

The increased competition in the US and Europe is largely due to the large number of trading venues within these jurisdictions, according to Menkveld (2011). The author continues that the number of trading venues and the resultant competition has reduced bid-ask spreads and therefore the transaction costs as well.

A growing trend over the last ten years or so has involved the consolidation of numerous regional and small international exchanges, particularly in Europe (Jain, 2003). Examples of such mergers include the formation of Euronext which consists of the exchanges within Amsterdam, Brussels and Paris, plus Scandinavian exchanges have also merged to form NASDAQ OMX (Jain, 2003). The proliferation of multiple trading venues especially within Europe was largely driven by the European Union's regulatory changes with the introduction of MiFID (Menkveld, 2011). The directive ultimately allowed national exchanges to compete, which encouraged new markets to appear (Menkveld, 2011).

With the introduction of trading venues such as BATS Chi-X Europe[2] and Turquoise[3] which both offer high speed access to stocks through low fee structures – two very attractive factors for market participants concerned about liquidity and narrow margins – these venues gradually encroached on market share held by LSE and NYSE Euronext (Europe) (Menkveld, 2011).

Speed is quickly becoming the currency of the markets. Hasbrouck and Saar (2013) state that speed is vitally important to traders due to the innate volatility of financial instruments. Speed also allows for the ultimate desire to create profitable opportunities by being the "quickest to market". This race has driven "speed players" to implement state-of-the-art technology and use of proximity or co-location services that allow immediate access to the market's trading engine. The authors suggest that the world of speed has now entered a millisecond domain where algorithms can respond to each other at speeds equivalent to 100 times faster than it would take a human to blink.

Brogaard (2010) supports this by citing Hendershott and Moulton (2007) who found that an average trade on NYSE took approximately ten seconds to execute, but due to technological advancements and the introduction of HFT, some firms are able to trade their entire strategy of buying and selling, multiples times within a mere second. Brogaard (2010) states that the reason for these very high speeds is twofold, namely the change from stock prices originally quoted in eighths to now being decimalised has created the opportunity for instant price variation. Because of the minute price changes, trading is less risky, as trading is done within

[2] A Multilateral Trading Facility (MTF) that offers a low cost trading venue for instruments listed on other major exchanges.
[3] An MTF that also offers a low cost trading venue for instruments listed on other major exchanges.

short investment/time horizons with price movements in cents as opposed to eighths of a US dollar.

However, contrasting results of a study by Hendershott and Moulton (2007), cited by Brogaard (2010) which examined the introduction of NYSE's Hybrid Market in 2006, found that reduction in latency due to the engine's expanded automatic execution and reduced execution time from ten seconds to less than one second, actually widened spreads but bettered information efficiency. However, Riordan and Storkenmaier (2012) found that a reduction in latency improved the liquidity on the Deutsche Boerse. Hasbrouck and Saar (2013), therefore suggest that the impact of a change in latency on market quality is really dependent on how much competition there is amongst liquidity suppliers and the ability of liquidity demanders to adopt algorithms and implement dynamic limit order strategies.

5.2 Algorithmic Trading (AT)

Algorithmic trading (AT) is a more complex version of electronic trading but which has set limitations determined by a set of rules. Brogaard (2010) differentiates between AT and HFT. Ultimately, AT is similar to HFT but fundamentally different in that AT has longer holding periods varying between trading: minutes, days, weeks and longer. The author notes that HFT is defined by holding positions for exceedingly short periods of time with the intention to end the day neutral. Hendershott, Jones and Menkveld (2011) explain that algorithms define the timing, price, quantity and order routing, whilst regulating market conditions for various securities and trading venues, ultimately reducing the market impact often experienced with the execution of large orders.

Hasbrouck and Saar (2013) state that not all algorithms play the same role in the market and that acknowledging algorithm objectives, could stimulate patterns in market data and impact market quality. Menkveld (2011) differentiates between agency and proprietary algorithms as not all algorithmic activity is the same. Typically, agency algorithms are utilised by buy-side institutions as they help to reduce the cost of executing trades by breaking up large orders into pieces that are then sent to multiple trading venues over a period of time (Menkveld, 2011). Naturally, such an arrangement is not currently possible within the South African market, as the JSE is the only domestic trading venue. The authors note that the main feature of agency algorithms is that much of the decision making in terms of which stocks to trade and the quantity to be traded, is done by the portfolio manager. The intention of these algorithms is to keep execution costs relative to a specific benchmark to a minimum

(Menkveld, 2011). These market participants, as explained by the authors, essentially demand liquidity even when their strategies might make use of non-marketable limit orders.

When looking at proprietary algorithms, they are considered more diverse and more difficult to categorise. The overarching characteristic though, remains speed. Hasbrouck and Saar (2013, p.1) refer to low latency trading as typically "strategies that respond to market events in the millisecond environment".

5.3 High Frequency Trading (HFT)

Deutsche Bank Research (2011) explains that the history of HFT started with electronic trading with the electronification of execution venues in the late 1990s which allowed market participants to gain remote access to electronic order books.

HFT can be seen as a subset or category of AT, where a large number of orders (of small size) are filtered into the market at incredible processing speeds (Brogaard, 2010). HFTs in essence take advantage of miniscule price disparities in the market but due to the high speed advantage, these participants are able to generate substantial profits (Deutsche Bank Research, 2011).

Deutsche Bank Research (2011) clarifies that HFT is not a trading strategy, instead it is considered to be a more technologically advanced way of applying certain trading strategies. Whether HFT improves liquidity is debateable as Deutsche Bank Research (2011, p.3) views the liquidity provided by these participants to be "opportunistic liquidity provision", as entering and exiting the market with a large position is very difficult.

Because of offerings such as co-location, where the market participant can place their servers in close proximity to the trading engine, HFT can take full force and blossom to its full potential. HFT players are known to transact in the market at incredible speeds whilst also generating the majority of the message activity (such as orders) in these capital markets.

5.3.1 HFT and Liquidity

Brogaard (2010, p.1) states that HFTs tend to argue that they enhance liquidity, improve price discovery and lower volatility, but contrasting views in the market believe that HFTs aggravate volatility, dry up liquidity and profit at the expense of investors considered to be more "traditional".

Brogaard (2010) also examined HFT market behaviour and found that HFTs trade securities with more significant market capitalisation, that have lower market-to-book ratios, more narrow spreads, less depth and much lower levels of non-HFT trading volume. In particular, the trading strategies employed are heavily dependent on past returns and past order imbalances. Many views exist around the actual effect on volatility when HFT activity is prevalent. Brogaard (2010) found that HFTs tend to lower their supply of liquidity somewhat and enlarge their need for liquidity as volatility increases on a daily basis.

Deutsche Bank Research (2011) cites studies by Hendershott and Riordan (2009) and Jovanovic and Menkveld (2010) who indicate that HFT, through market making and arbitrage strategies, had indeed enhanced liquidity, narrowed spreads and helped to align market prices across various trading venues/markets. According to the research team, little to no research supports the notion that HFT does not contribute towards liquidity. A noteworthy argument though, is that HFTs generally only trade instruments that have a certain level of liquidity that is lucrative for the trader, that is, liquidity begets liquidity. Deutsche Bank Research (2011), however, highlight some key concerns:

a) there is no obligation from the HFT to provide market making duties;
b) due to the small sizes of HFT orders, they contribute a limited amount to market depth; and
c) because of the short duration, liquidity might be accessible before these orders are cancelled so HFT quotes are hardly accessible.

5.3.2 HFT and Market Quality

Apart from liquidity, Brogaard (2010) also examined whether HFT contributes to price formation/discovery within equity markets.

A contentious point around HFT is whether it employs an investing strategy that is engaged in front-running. Brogaard (2010) believes that HFTs are in the position to sense when other market participants anticipate a large order of securities and thus enter into the same position as these other market participants before they are able to transact. The end result, because of this interception, would mean that costs are driven up to a level where non-high frequency traders transact the preferred transaction (Brogaard, 2010). The author concludes in his findings that HFTs are seen as a collective are therefore not using front-running as their key strategy. However, he is unable to conclude that there is no front-running either so the results regarding front-running are therefore inconclusive.

To determine whether HFTs use similar strategies to aggravate market movements, Brogaard (2010) looks at the frequency at which HFTs trade with each other and cites the benchmark model used by Chaboud, Hjalmarsson, Vega, and Chiquoine (2009). The author concludes that HFTs take part in a much smaller diverse group of strategies than when compared to non-HFTs. Rather, the diverse strategies result in one HFT opting to buy and another HFT to sell at the same time (Brogaard, 2010).

Hasbrouk and Saar (2013) investigate the impact of high frequency trading on the market environment through a newly designed measure. The measure looks at how low latency trading activity changes during periods of normal continuous trading, when prices decline significantly and when economic uncertainty is intensified. The results show that greater levels of low latency trading aids in narrowing bid-ask spreads, strengthening the depth of the central order book and also decreases short-term volatility.

Even though the general consensus regarding the impact that low latency activity have on market quality, is positive, Brogaard (2010) and Brogaard, Hendershott and Riordan (2012), cited by Menkveld (2011), note that low latency activity could impact the market negatively during times of significant market stress. The example of the "Flash Crash" on 6 May 2010 is a prime example of how some believe high frequency trading created difficulties within the operations of the NYSE Equity Market.

6 DATA AND METHODOLOGY

The data sample in this research includes data for ZA01 (Top 40), ZA02 (Mid Cap) and ZA03 (Less Liquid) stocks listed on the JSE Equity Market, for the period 2 July 2005 to 1 July 2013. This particular data period was selected due to data availability and due to that the fact that it covered events such as the JSE trading engine upgrade in 2007, the occurrence of the Global Financial Crisis (GFC) and the second JSE trading engine upgrade in 2012. For purposes of simplicity, only ordinary shares are considered in the data sample, as these instruments comprise the majority of the traded instrument types on the exchange. The stocks vary in liquidity with ZA01 typically viewed as the most liquid shares listed on the JSE, ZA02 the second most liquid and ZA03 the least liquid.

Continuity is important, therefore stocks that were not listed for every year during the sample period were removed from the sample data. In addition, the ILLIQ measure was used as the benchmark therefore if a particular stock returned a zero average for each year in question, this stock too was removed from the sample. In cleaning the data this way, the number of eligible stocks in the sample decreased from roughly 400 stocks per year to 91 stocks that remained listed throughout the data sample period. Another point to consider is that the sample data used includes central order book data and off-order book data (reported trades), whereas some liquidity measurements (Average Spread) only include central order book data. Therefore, liquidity measurements such as the Average Spread and JSE Liquidity (which excludes reported trades) will be a better central order book liquidity measurement. This creates the challenge that the comparison of the liquidity measurements against each other will not be based on an equal footing. However, because the majority of all JSE Equity Market activity occurs within the central order book, there is still some comfort from knowing that a liquidity comparison will be possible.

The purpose of the analysis is to determine whether liquidity improved or diminished over the data sample period using different liquidity measurements, whether these liquidity measurements are in any way connected to each other and lastly whether the trading engine upgrade in 2012 and the introduction of low latency trading strategies improved liquidity. The analysis of the data is divided into four parts.

a) Part one: Each measurement of liquidity mentioned on the next page is calculated for each July-to-July year starting 2 July 2005 to 1 July 2013. In doing so, the intention is to examine the liquidity trends following the trading engine upgrade in July 2007, the GFC and the second trading engine upgrade in July 2012. In addition an ANOVA analysis is also conducted for each measurement with the intention of examining whether the implementation of the second trading engine upgrade and its impact on liquidity was statistically significant:

a. Amihud's illiquidity ratio (ILLIQ) during each July-to-July year;
b. Turnover ratio during each July-to-July year;
c. Average daily value traded per stock during each July-to-July year;
d. Average market capitalisation of each stock during each July-to-July year;
e. Average spread per instrument for each July-to-July year;
f. JSE Liquidity measurement – a JSE calculated liquidity measurement adjusted for each July-to-July year.

b) Part two: Each ordinary share is ranked from most to least liquid using each aforementioned liquidity measurement for each July-to-July year starting 2 July 2005 to 1 July 2013. These liquidity rankings are then correlated with each other for each July-to-July year, with the intention to ascertain whether the different liquidity measurements are in any way related or connected to each other.

c) Part three: An event study is conducted for the period 1 July 2011 to 1 July 2013. The intention of the study is to examine whether the introduction of the trading platform Millennium Exchange™ had any impact on the returns of a ZA01, ZA02 and ZA03 portfolio of instruments. If the impact on portfolio returns is statistically significant, it can be interpreted that the trading engine did indeed have an effect on stock returns and that in turn liquidity was affected as well.

d) Part four: Lastly, the so-called "computer trading" trading activity and its effect on liquidity will be examined. Due to the JSE's data limitations, algorithmic trading activity or HFT cannot be explicitly identified and thus this low latency type of trading is referred to as "computer trading" based on assumptions such as certain levels of message (order) traffic. The intention is to deduce a positive relationship between improved technology, resultant "computer trading" and liquidity.

7 ANALYSIS AND RESULTS

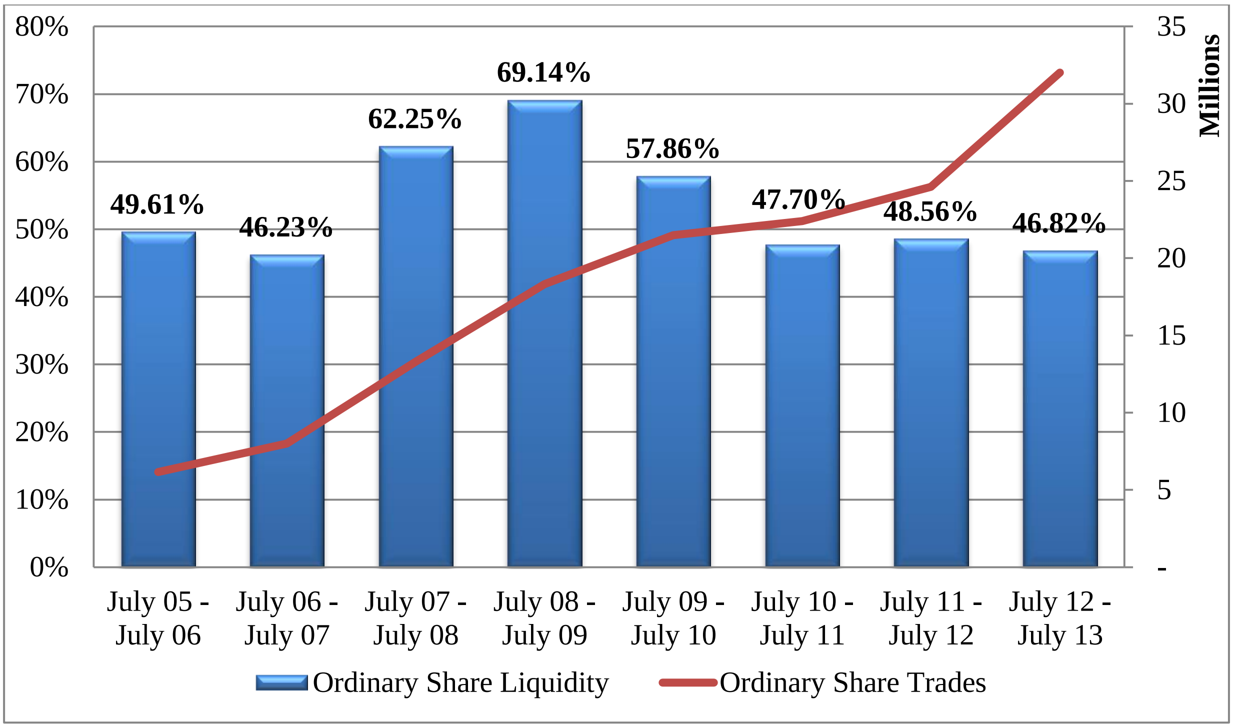
Before examining the results of the analysis, it is important to perhaps take note of Amihud (2002) who stated that any attempt to capture liquidity in a single variable is particularly difficult and unnecessary as illiquidity is a function of a number of variables each considered a proxy for liquidity. With this in mind, one has to take note that trying to isolate certain events and subsequently attempting to pinpoint these events as the catalysts for improved or diminished liquidity levels, remains a challenge. However, it is hoped that the result of the analysis will still offer some insight and evoke some interesting questions.

When considering the JSE Equity Market liquidity levels, particularly for ordinary shares (most traded instrument type on the JSE), there appears to be a slight decrease since July 2009 shown in Figure 1 on the following page. The liquidity measure used is one calculated by the JSE.

Figure 1 shows an inverse relationship between the JSE Equity Market liquidity levels for ordinary shares and the number of ordinary share transactions (trades) from July 2005 to July 2013. Initially, one would be under the impression that liquidity would have increased considering how trading volumes have increased dramatically over the same period. An active market would surely translate into a liquid market based on this assumption.

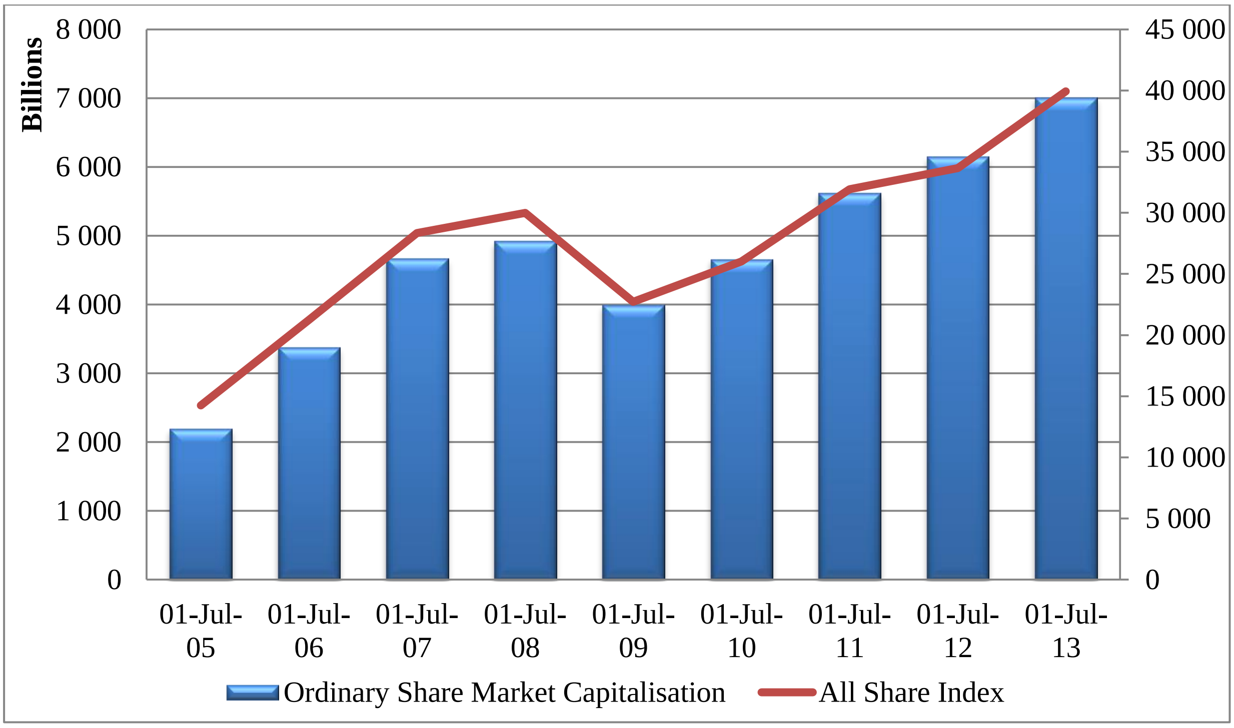
Figure 1: Ordinary Share Liquidity vs. Ordinary Share Transactions

(2 July 2005 - 1 July 2013)



Given some of the constraints within the JSE data, it is difficult to determine whether the higher liquidity levels during 2008 and 2009 were due to the dark side of liquidity as mentioned by Wuyts (2007), that is, liquid markets consist of investors that no longer focus on fundamentals but rather have a short-term view regarding their investment decisions. Perhaps in examining the growth of orders on the JSE Equity Market, it is appropriate to suggest that traders are looking to flood the market with excessive orders in order to make small profits and therefore are not particularly focused on fundamentals. Deutsche Bank Research (2011) mentions particularly that HFT which is considered a subset of algorithmic trading (AT) aims to submit large number of orders at significant speeds and take advantage of very small price movements. Unfortunately, JSE order or trade data is not defined as either HFT or AT and therefore a number of assumptions needed to be made in order to infer low latency trading, which is discussed later in this chapter.

Figure 2: JSE Equity Market Market Capitalisation for Ordinary Shares vs. All Share Index (1 July 2005 - 1 July 2013)



Apart from increased trading volumes, the market capitalisation of JSE ordinary shares also boomed to record levels along with record JSE All Share Index levels, seen in Figure 2 above.

With all these positive elements clearly indicating a robust and active market, why is it that liquidity levels appear to have started to diminish? A simple answer might lie with the formula used to determine liquidity levels, where increasing market capitalisation is inversely correlated with liquidity. One therefore has to ask whether such measurements actually offer insight into the "intrinsic" liquidity of a market.

It is quite evident that liquidity, in its entirety, is firstly a complex concept and secondly that it clearly comprises of numerous factors. It is hoped that this study will shed some light on the different liquidity measures currently used and how fundamental changes in technology, which clearly have a beneficial effect on trading volumes, have the same beneficial effect on liquidity levels.

7.1.1 Liquidity Measurements Compared

7.1.1.1 Amihud's Illiquidity Ratio (ILLIQ)

As mentioned, Figure 1 shows diminishing ordinary share liquidity levels, using the JSE Liquidity measurement which includes all trade types (central order book and off-order book trades). Now, using the ILLIQ ratio as the liquidity measurement per ordinary share within the sample period, liquidity is once again examined.

Figure 3 that follows shows how the yearly ILLIQ ratio has changed per instrument for each July-to-July year. Spikes in illiquidity (shown in red circles) are particularly evident for individual stocks Village Main Reef (VIL), African Dawn Capital (ADW) and ISA Holdings (ISA) from 2 July 2007 to 1 July 2010. Stocks such as VIL, ADW and ISA are relatively small in relation to market capitalisation, have small daily average trades and their average spreads are typically larger than the more liquid Top 40 stocks. Hence, the apparent spikes in illiquidity as any relatively change in daily value traded or closing price would mean a large variance in the illiquidity of these smaller stocks.

Figure 4 offers a time series view of the average daily ILLIQ ratio for the total data sample period. Illiquidity was particularly more evident from about March 2008 to September 2010 based on the large outliers during this period (shown in the red circle). However, this period was synonymous with the GFC period. Following this time period, the number of ILLIQ ratio outliers decreased noticeably, even more so after the trading engine upgrade in July 2012.

Figure 5 shows that the average yearly ILLIQ ratio has decreased steadily over the data sample period. Apart from a large spike during 2 July 2007 - 1 July 2008 (shown in red circle), liquidity seemed to strengthen. Following another, but more moderate peak in illiquidity during 2 July 2010 - 1 July 2011 (shown in red circle), illiquidity settled at much lower levels during the subsequent two July-to-July years, again particularly during the period of the trading engine upgrade. Overall, it would appear that liquidity levels improved when using this measurement, it would however be presumptuous to think that the sole reason for this was the trading engine upgrade before examining the other liquidity measurements as well and also conducting a one way ANOVA exercise to determine differentiation between each July-to-July year.

The standard deviation of the yearly ILLIQ ratio, in Table 2, appears much greater during 2 July 2007 - 1 July 2009 and then again during 2 July 2010 - 1 July 2011. This is in line with the observed outliers in Figure 4 and 5. The averages for each July-to-July year group are fairly similar, with the exception of the periods 2 July 2007 - 1 July 2009 and then again during 2 July 2010 - 1 July 2011.

Table 2: Summary Results for Yearly ILLIQ Ratio

Groups	Count	Sum	Average	Standard Deviation
2 July 2005 - 1 July 2006	91	0.00007509	0.00000083	0.00000372
2 July 2006 - 1 July 2007	91	0.00005734	0.00000063	0.00000305
2 July 2007 - 1 July 2008	91	0.00027356	0.00000301	0.00002398
2 July 2008 - 1 July 2009	91	0.00021039	0.00000231	0.00001082
2 July 2009 - 1 July 2010	91	0.00000590	0.00000006	0.00000030
2 July 2010 - 1 July 2011	91	0.00020551	0.00000226	0.00001704
2 July 2011 - 1 July 2012	91	0.00002699	0.00000030	0.00000111
2 July 2012 - 1 July 2013	91	0.00002277	0.00000025	0.00000117

The results of the one-way ANOVA in Table 3 show how the average yearly ILLIQ ratios are either different or the same from one July-to-July year group to the next. We state that the null hypothesis is that the average yearly ILLIQ ratio for each July-to-July year is the same. In other words, the trading engine upgrade has had no significant impact on the average yearly ILLIQ ratio for each July-to-July group. The one-way ANOVA results attempt to show that the null hypothesis can either be rejected or not rejected.

Table 3: ANOVA Results for Yearly ILLIQ Ratio

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.000000001	7	0.00000000012	0.937	0.477	2.022
Within Groups	0.000000091	720	0.00000000013			
Total	0.000000092	727				

In examining the p-value (0.477) the results show that it is greater than 0.05 and therefore the null hypothesis is not rejected and is not statistically significant. It can therefore be determined that the average ILLIQ ratio between the July-to-July groups is the same. In the same way, the F-statistic of 0.937 is less than the F-critical value and therefore again the null hypothesis is not rejected. With this in mind it can be inferred that the implementation of the new trading engine in July 2012 did not impact the average yearly ILLIQ ratio between each July-to-July year group, and therefore did not impact liquidity. It is important to remember that ILLIQ as Amihud (2002, p.32) explains it, is the "daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact". Indirectly one could say that the ANOVA results show that the trading engine implementation did perhaps not bring with it significant share price movements/changes, due to the efficiencies within the market and liquidity therefore remained relatively consistent.

Figure 3: Yearly ILLIQ Ratio per Ordinary Share (2 July 2005 - 1 July 2013)

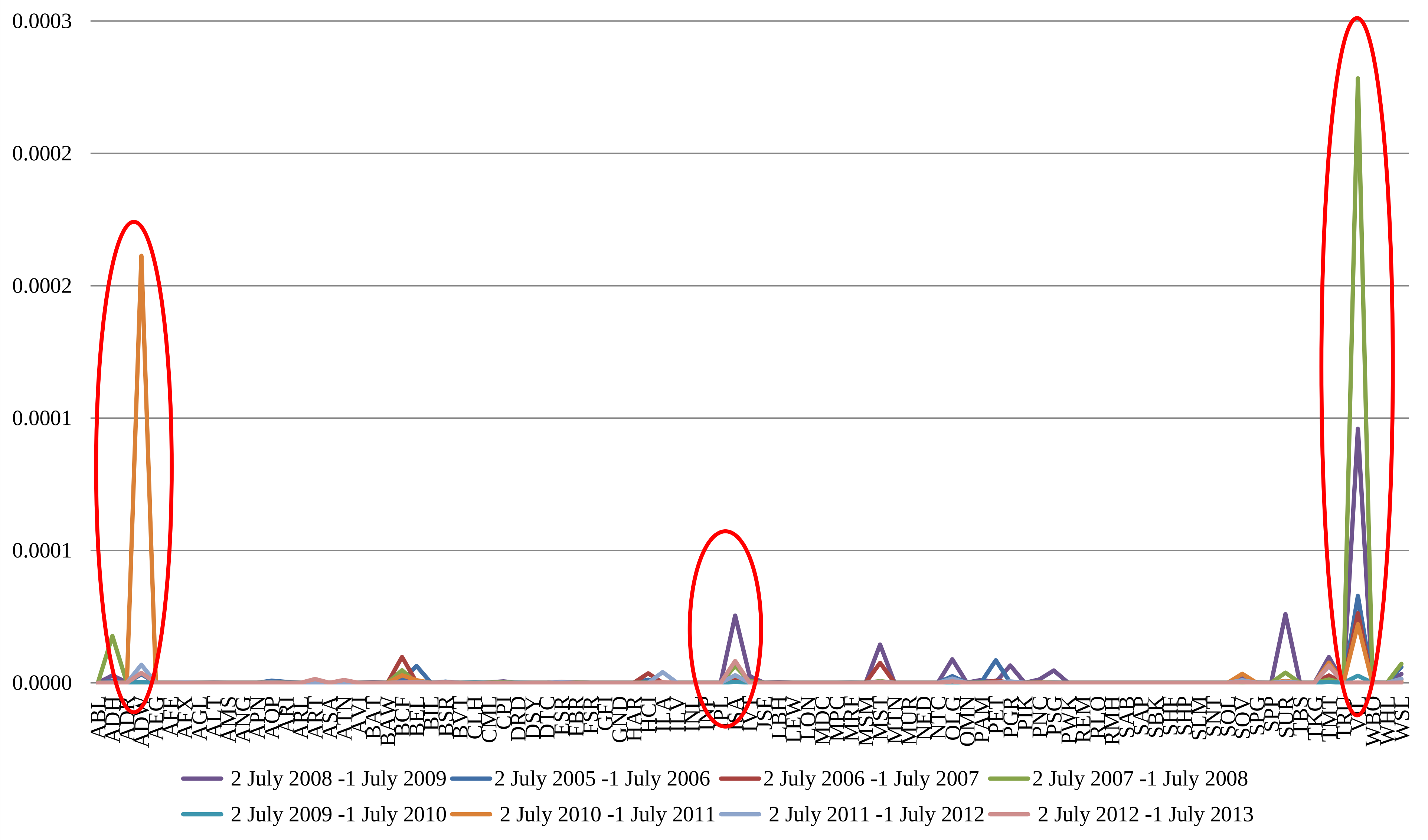


Figure 4: Average Daily ILLIQ Ratio (2 July 2005 - 1 July 2013)

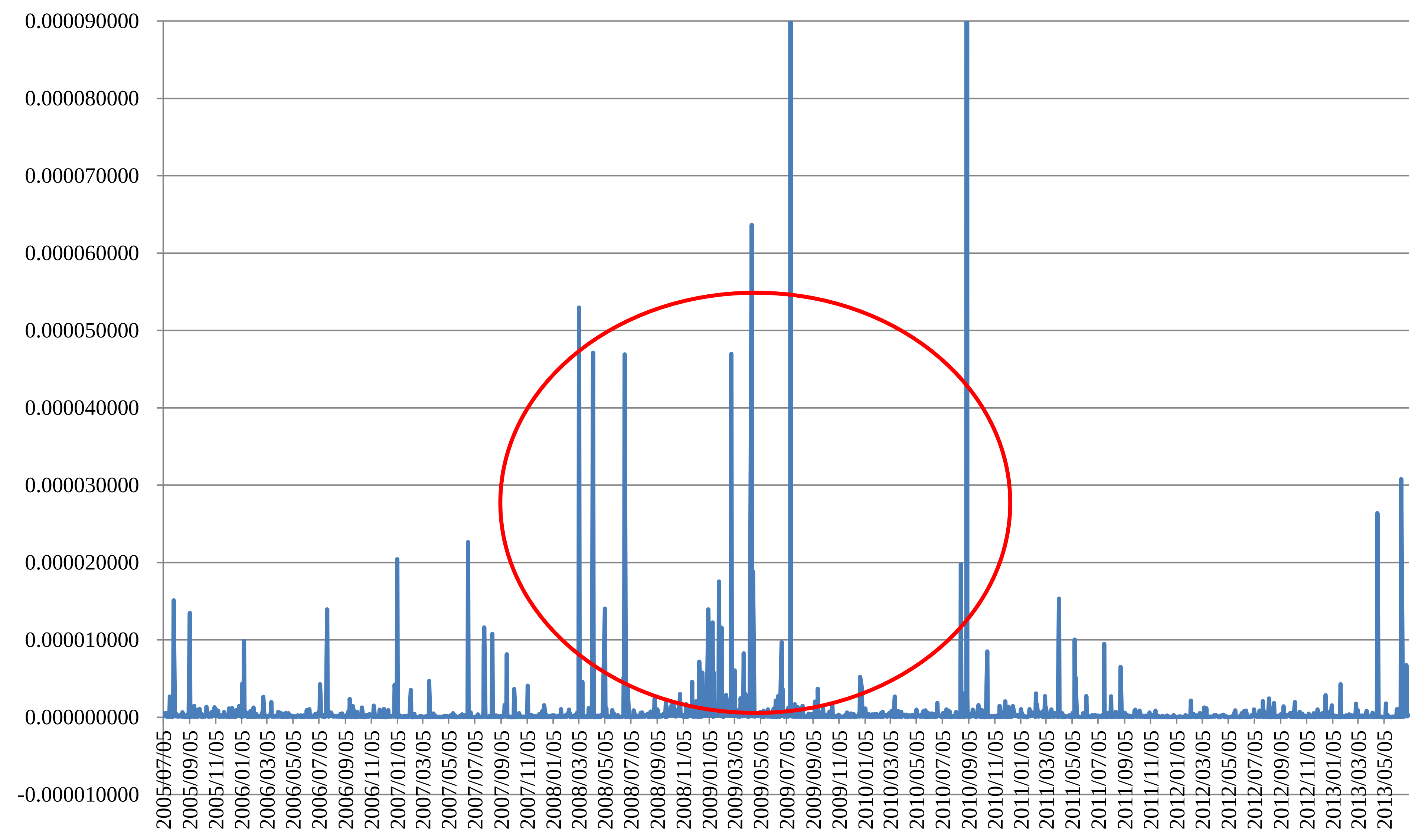
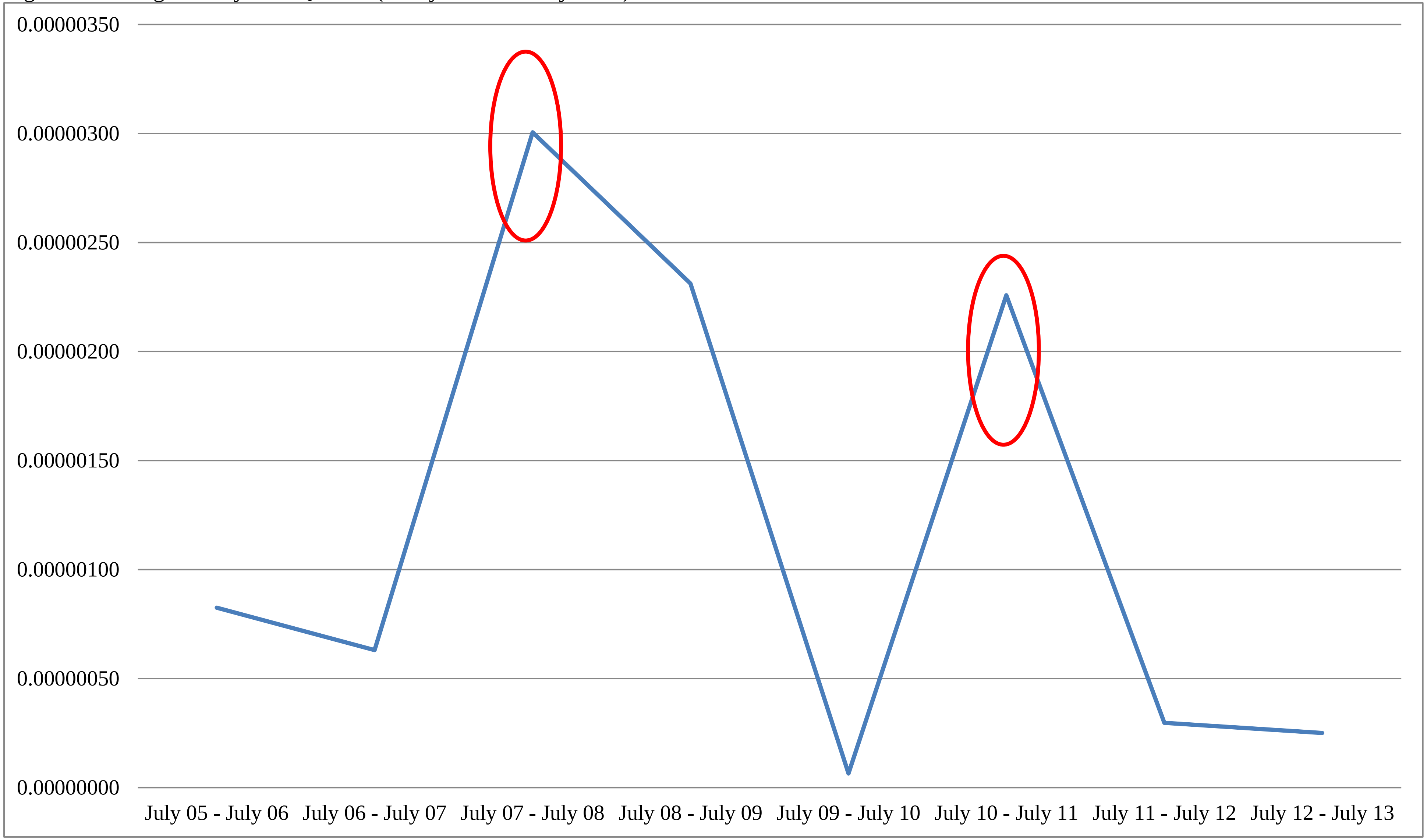


Figure 5: Average Yearly ILLIQ Ratio (2 July 2005 - 1 July 2013)



7.1.1.2 Turnover Ratio

The average turnover ratio appears very volatile during the data sample period. In examining the standard deviation in Table 4, it would appear that the ratio is particularly erratic during 2 July 2007 - 1 July 2010. This is expected as it was during this time period that the GFC came into full force. However, the subsequent volatility levels then revert to levels last seen during 2 July 2005 - 1 July 2007.

Table 4: Standard Deviation of Average Turnover Ratio (2 July 2005 - 1 July 2013)

	2 July 2005 - 1 July 2006	**2 July 2006 - 1 July 2007**	**2 July 2007 - 1 July 2008**	**2 July 2008 - 1 July 2009**	**2 July 2009 - 1 July 2010**	**2 July 2010 - 1 July 2011**	**2 July 2011 - 1 July 2012**	**2 July 2012 - 1 July 2013**
Standard Deviation	0.0013	0.0013	0.0016	0.0019	0.0016	0.0013	0.0012	0.0013

Figure 6 shows that average yearly turnover ratio is particularly erratic, therefore making the observation of a general trend particularly difficult. When observing VIL, ADW and ISA (in red circles), it is evident that these stocks do not appear as particular outliers as was the case with the ILLIQ ratio. Instead, the likes of Aveng Limited (AEG), Barloworld Limited (BAW) and Murray and Roberts Holdings Limited (MUR) (in the red circles) prove to be the biggest peaks in Figure 6. All three stocks are medium liquid securities, forming part of ZA02.

Figure 7 shows the average daily turnover ratio during the data sample period. There is a peaked average yearly turnover ratio from about July 2007 to July 2010 (shown in the red circle), however, as is expected this declines as the GFC progressed. The average yearly turnover ratio then also slightly picks up from 2 July 2012 following the implementation of the JSE trading engine upgrade, as seen by the 22-day moving average trend line. Again, similarly to the ILLIQ ratio results, it would appear that the average yearly turnover ratio (and with that, liquidity) has increased following the trading engine upgrade in July 2012.

The average yearly turnover ratio, shown in Figure 8, highlights the peaks in liquidity (shown in the red circles) during 2 July 2007 - 1 July 2009. The average yearly turnover ratio following the trading engine upgrade in 2012 is fairly similar to the levels seen at the beginning of the data sample period.

The standard deviation of the average yearly turnover ratio, in Table 5, appears much greater during 2 July 2007 - 1 July 2010. This is in line with the observed volatility in Figure 7. The averages shown in Table 5 for each July-to-July year group are also fairly similar.

Table 5: Summary Results for Average Yearly Turnover Ratio

Groups	Count	Sum	Average	Standard Deviation
2 July 2005 - 1 July 2006	91	0.18427209	0.00202497	0.00125600
2 July 2006 - 1 July 2007	91	0.19108346	0.00209982	0.00126852
2 July 2007 - 1 July 2008	91	0.22650418	0.00248906	0.00159715
2 July 2008 - 1 July 2009	91	0.23199763	0.00254942	0.00186828
2 July 2009 - 1 July 2010	91	0.21245452	0.00233467	0.00159119
2 July 2010 - 1 July 2011	91	0.18081542	0.00198698	0.00128210
2 July 2011 - 1 July 2012	91	0.17956403	0.00197323	0.00123491
2 July 2012 - 1 July 2013	91	0.19034187	0.00209167	0.00131152

The results of the one-way ANOVA in Table 6 shows how the average yearly turnover ratios are either different or the same from one July-to-July year group to the next. Again, the same null hypothesis is used, namely that the average yearly turnover ratio for each July-to-July year is the same. In other words, the trading engine upgrade has had no significant impact on the average yearly turnover ratio for each July-to-July group.

Table 6: ANOVA Results for Average Yearly Turnover Ratio

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.000034	7	0.0000048	2.328	0.024	2.022
Within Groups	0.001498	720	0.0000021			
Total	0.001532	727				

In examining the p-value (0.024) the results show that it is less than 0.05 and therefore the null hypothesis is rejected and is statistically significant at the 0.05 level. It can therefore be determined that the average yearly turnover ratio between the July-to-July groups is not the same. In addition, F-statistic of 2.328 is greater than the F-critical value and therefore the null hypothesis is rejected and the F-statistic is deemed statistically significant at 0.05. It can therefore be inferred that implementation of the new trading engine in July 2012 did impact the average yearly turnover ratio between each July-to-July year group and therefore impacted liquidity as well. Again, the turnover ratio looks at how frequently the number of shares per stock is traded in comparison to the total number of shares available. One could perhaps indirectly argue that the introduction of the trading engine and its technology allowed market participants easier and quicker access and exit to/from the market – bringing with it higher trade volumes and therefore greater liquidity.

Figure 6: Average Yearly Turnover Ratio per Ordinary Share (2 July 2005 - 1 July 2013)

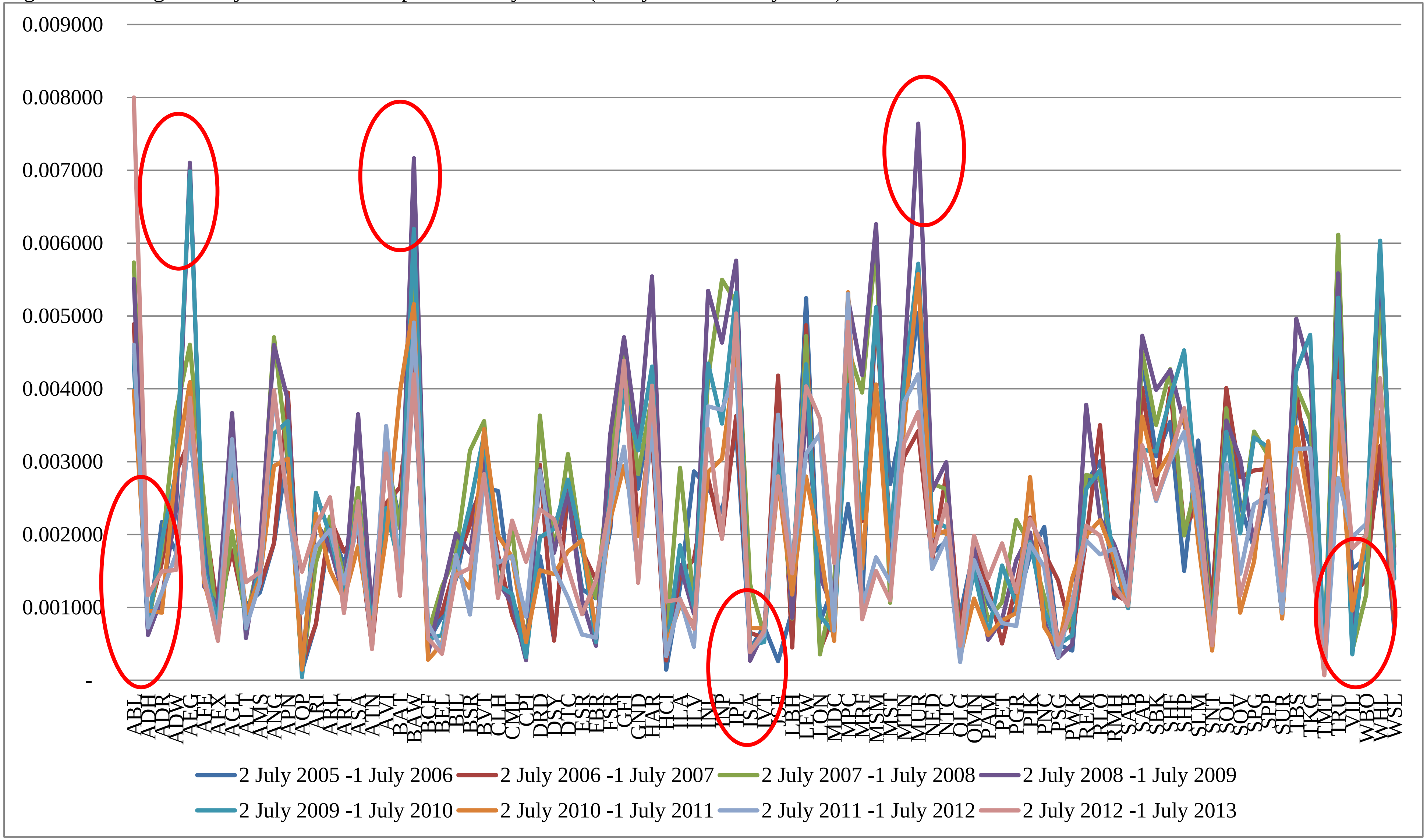


Figure 7: Average Daily Turnover Ratio (2 July 2005 - 1 July 2013)

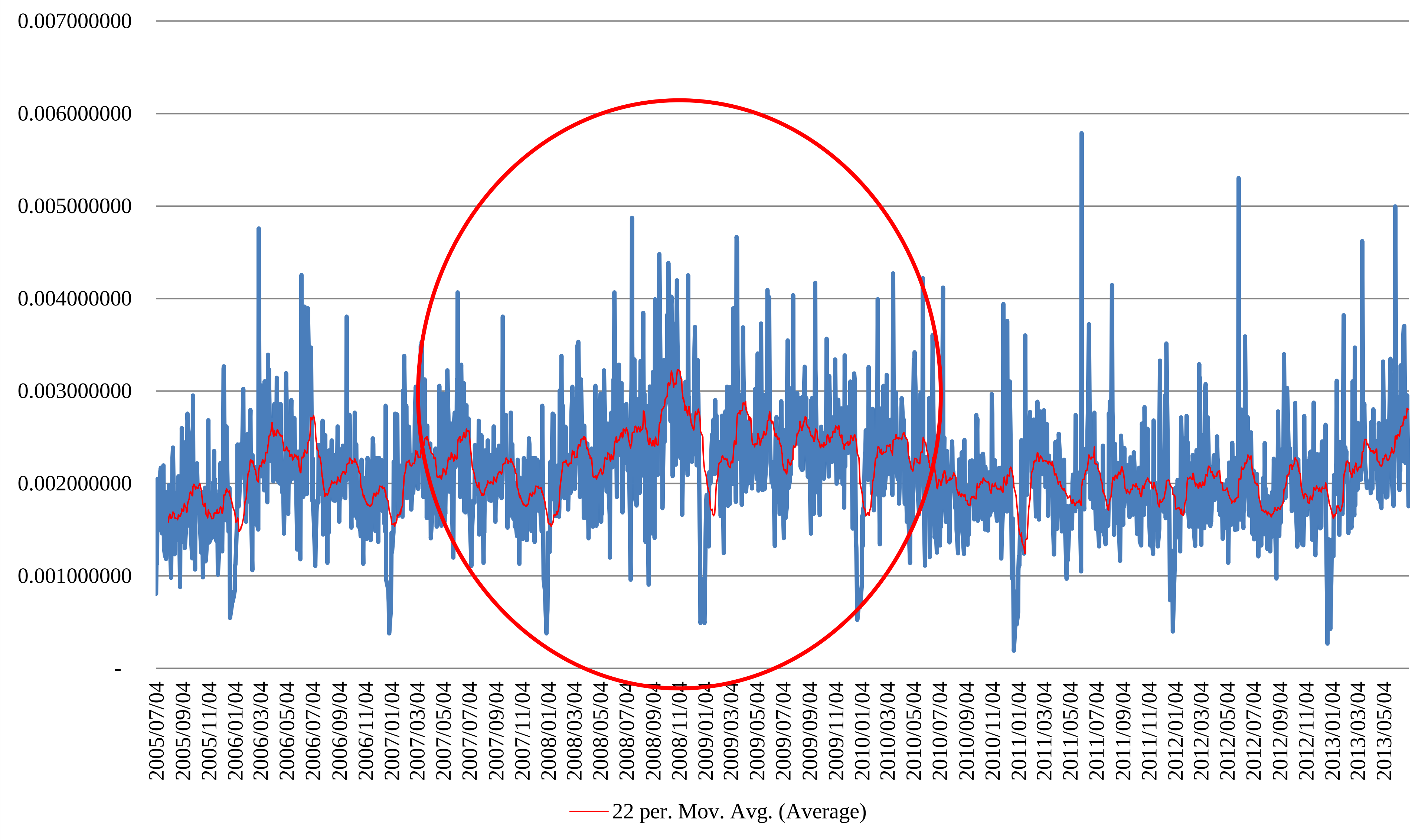


Figure 8: Average Turnover Ratio (2 July 2005 - 1 July 2013)

7.1.1.3 Average Daily Value Traded

Though difficult to deduce any particular trend, the JSE Equity Market's average daily value from 2 July 2005 - 1 July 2007 increased by roughly 26% and then again by another 41% in the following year. The subsequent July-to-July years showed decreased average daily value traded and only started seeing an increase in average value traded from 2 July 2011 - 1 July 2013.

Figure 9 shows the average daily value traded per ordinary share during the data sample period. It is evident when examining the entire sample period that there does not appear to be an increased number of different securities that now have amplified average daily value traded figures. Instead, it appears to be the same securities that are traded from 2 July 2005 - 1 July 2013, in just higher average daily values. These include the likes of Anglo American (AGL), BHP Billiton (BIL), MTN, SABMiller (SAB) and Sasol (SOL) as indicated by the red circles. Noticeably, these instruments are not the same outliers when the ILLIQ ratio and the turnover ratio were examined. Instead, these instruments are the most liquid shares on the JSE, which have high value traded figures and large market capitalisation figures.

Figure 10, shows the time series view for the daily value traded during the data sample period. The daily value traded during this data sample period seemed particularly heightened during 2 July 2007 - 1 July 2008 and then again from 2 July 2012 - 1 July 2013 (shown in the red circles). In particular, the 22-day moving average for the latter period seems to suggest an upward trend. This is interesting; as it is particularly during these aforementioned periods that the JSE implemented new trading engine technology. Figure 11 shows the average daily value traded for each July-on-July period with two peaks in particular, namely during 2 July 2007 - 1 July 2008 and then again from 2 July 2012 - 1 July 2013 (shown in the red circles).

The standard deviation of the average daily value traded, in Table 7, appears much greater during 2 July 2007 - 1 July 2008 and then again during 2 July 2011 - 1 July 2013. This appears to agree with the observed volatility in Figure 10. The averages shown in Table 7 for each July-to-July year group also vary greatly, with only some groups showing similar average figures.

Table 7: Summary Results for Average Daily Value Traded

Groups	Count	Sum	Average	Standard Deviation
2 July 2005 - 1 July 2006	91	R 5 461 235 362	R 60 013 575	R 116 479 424
2 July 2006 - 1 July 2007	91	R 6 905 068 897	R 75 879 878	R 149 412 810
2 July 2007 - 1 July 2008	91	R 9 736 370 059	R 106 993 078	R 220 029 362
2 July 2008 - 1 July 2009	91	R 8 625 586 118	R 94 786 661	R 198 193 797
2 July 2009 - 1 July 2010	91	R 8 517 416 342	R 93 597 982	R 190 179 383
2 July 2010 - 1 July 2011	91	R 8 549 775 722	R 93 953 579	R 193 405 086
2 July 2011 - 1 July 2012	91	R 9 425 985 044	R 103 582 253	R 217 221 306
2 July 2012 - 1 July 2013	91	R 10 236 759 904	R 112 491 867	R 204 340 792

Again, following the same approach with the ILLIQ ratio and the turnover ratio, a one-way ANOVA exercise is done for average daily value traded. The results of this exercise in Table 8 show how the average daily value traded are either different or the same from one July-to-July year group to the next. The same null hypothesis is used, namely that the average daily value traded for each July-to-July year is the same, thus implying that the trading engine upgrade has had no significant impact on the average daily value traded between each July-to-July group.

Table 8: ANOVA Results for Average Daily Value Traded

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	188 595 044 107 837 000	7	26 942 149 158 262 500	0.753	0.627	2.022
Within Groups	25 748 939 244 364 500 000	720	35 762 415 617 172 900			
Total	25 937 534 288 472 300 000	727				

The p-value (0.627) in the results Table 8, show that it is greater than 0.05 and therefore we fail to reject the null hypothesis where the p-value is not statistically significant at the 0.05 level. It can therefore be deemed that the average daily value traded between the July-to-July groups is the same. In addition, the F-statistic of 0.753 is less than the F-critical value and again we fail to reject the null hypothesis where F-statistic is not deemed statistically significant at 0.05. It can therefore be expressed that the evidence at hand shows that the implementation of the new trading engine in July 2012 did not impact the average daily value traded between each July-to-July year group and therefore liquidity was not affected either. The ANOVA results for average daily value traded are in line with the ANOVA results of the

ILLIQ ratio. It could therefore be inferred that the average daily value traded during the trading engine implementation period was perhaps due to increased share prices, as a result of market demand and supply forces. Liquidity therefore remained fairly uninfluenced by the trading engine upgrade.

Figure 9: Average Daily Value Traded per Ordinary Share (2 July 2005 - 1 July 2013)

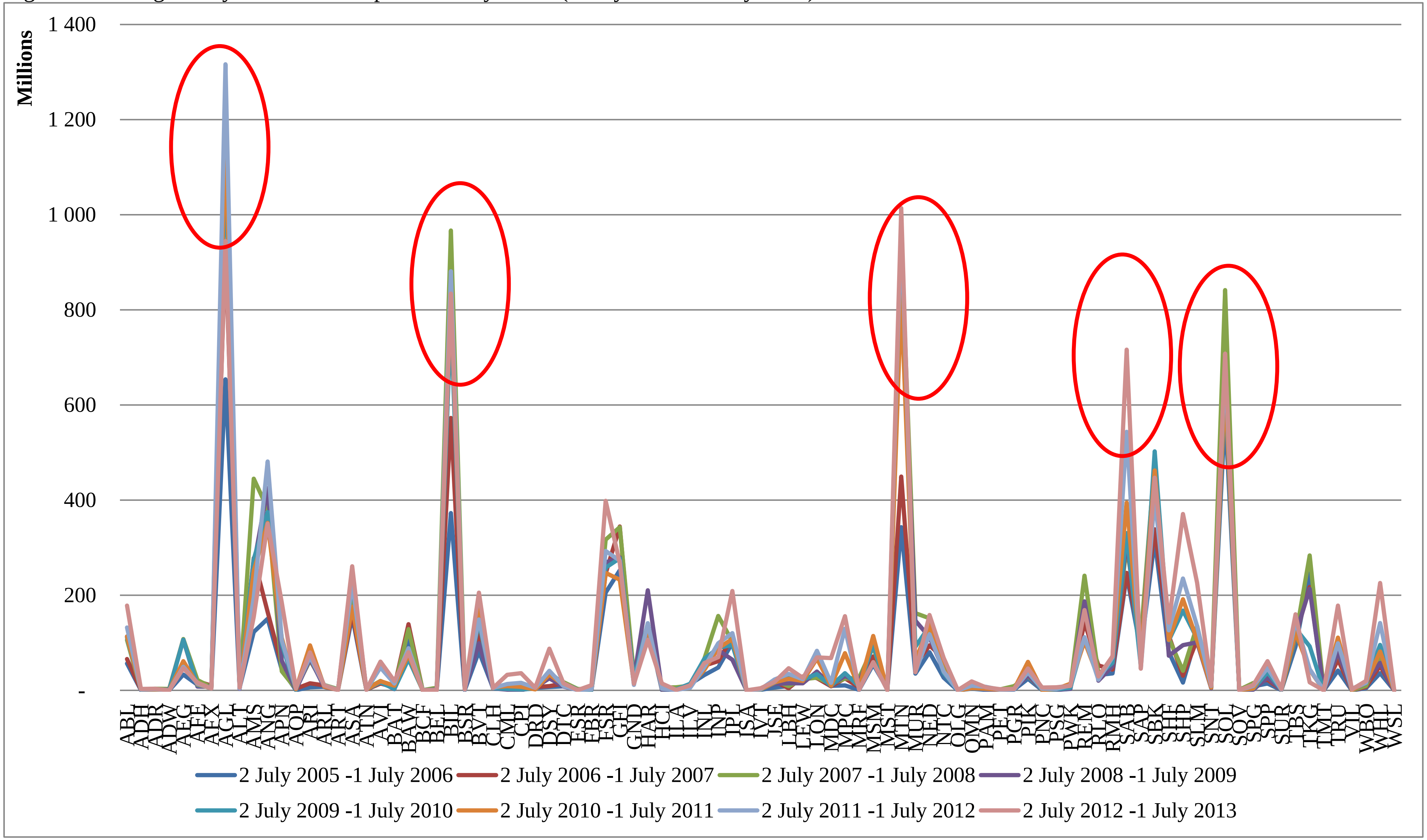


Figure 10: Daily Value Traded (2 July 2005 - 1 July 2013)

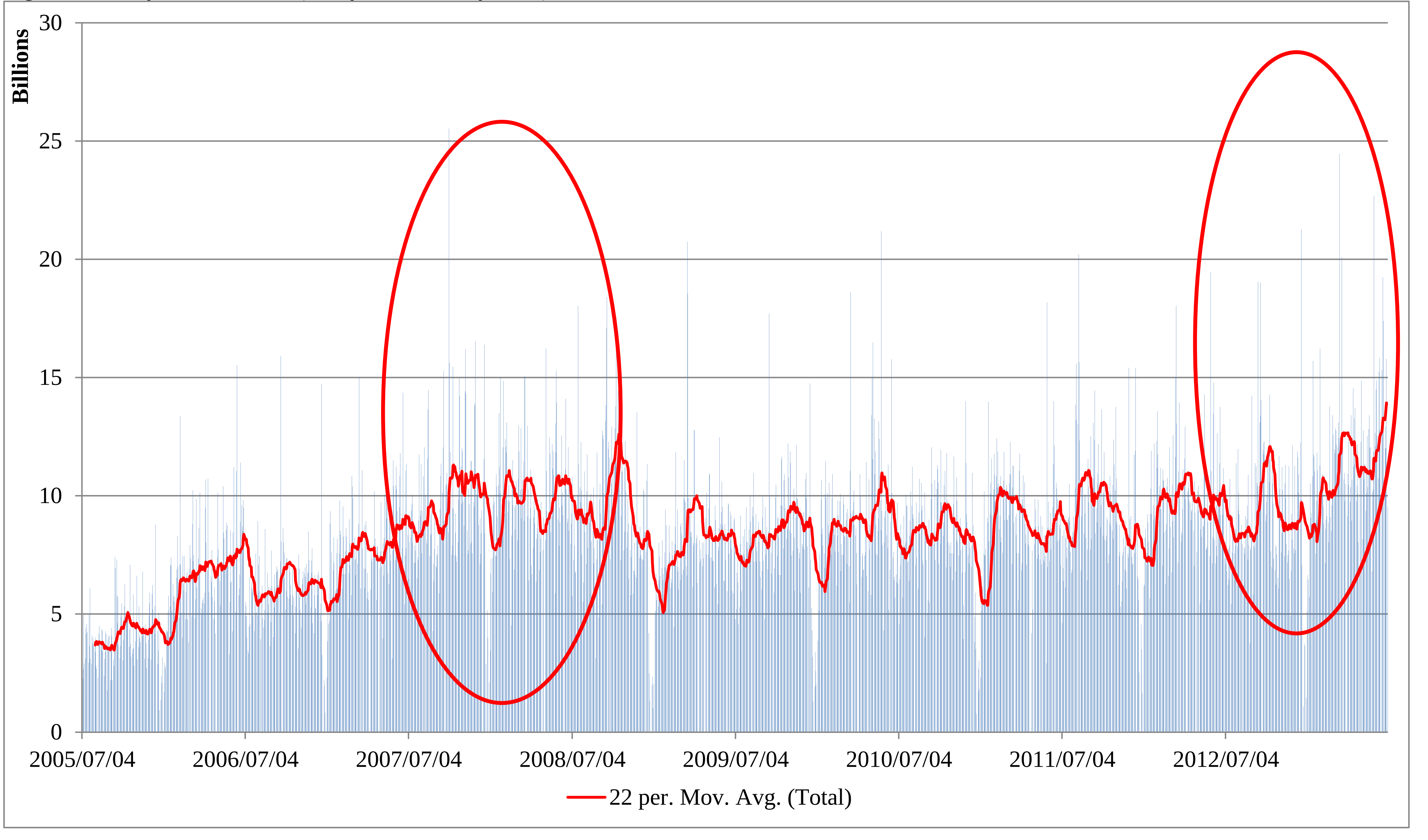
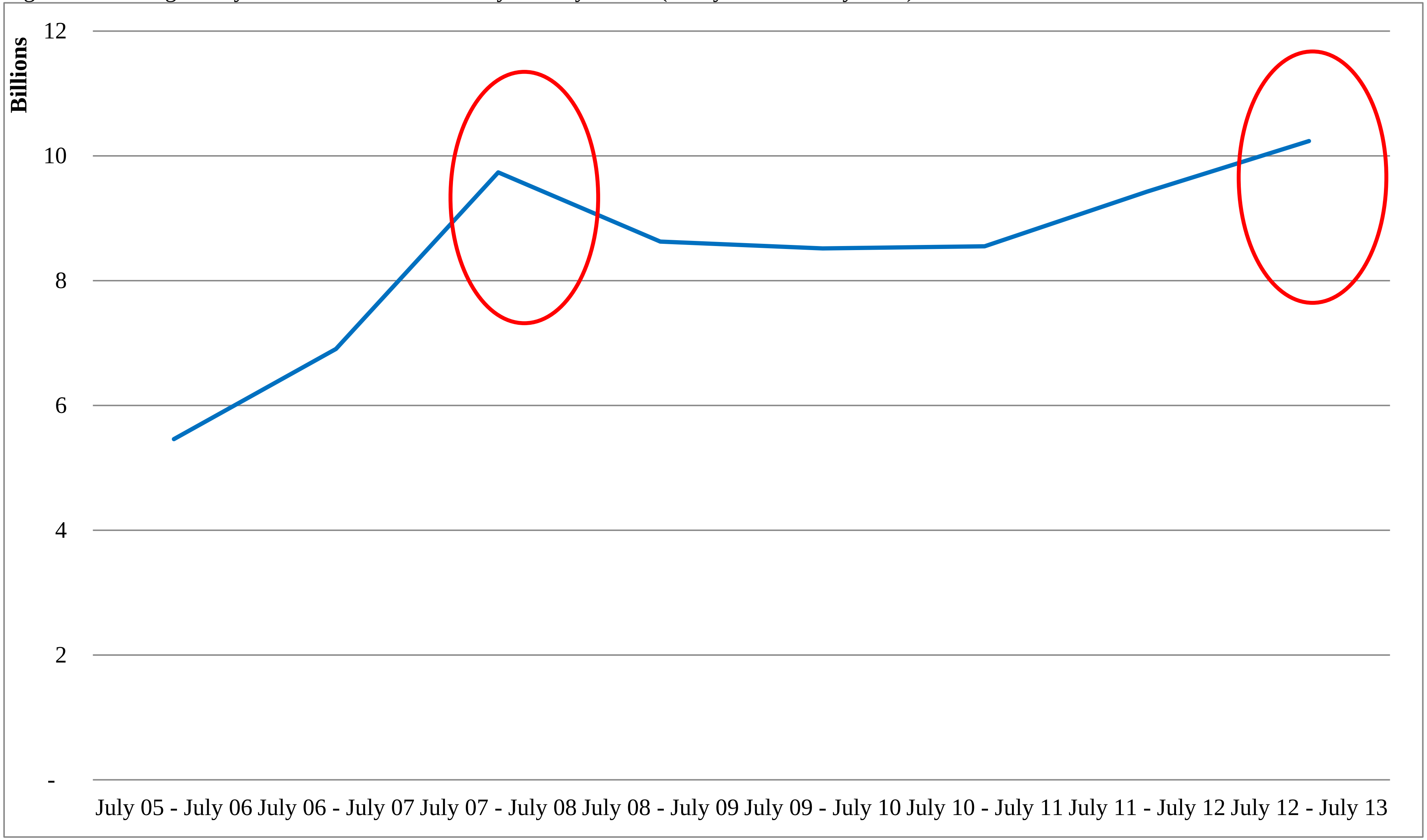


Figure 11: Average Daily Value Traded for each July-on-July Period (2 July 2005 - 1 July 2013)



7.1.1.4 Average Market Capitalisation

It is predominately the small-cap companies, such as ADW, Basil Read Holdings (BSR) and VIL (shown in red circles) that showed the biggest average market capitalisation growth during the data sample period, as seen in Figure 12. The growth in average market capitalisation for the remaining stocks within this data sample for the same data period appeared relatively flat in comparison. These excessive growth (and decline) figures for the aforementioned three stocks, though seemingly extreme, are based on small market capitalisation figures and therefore when compared with the likes SABMiller (SAB), BIL and AGL appear as large changes. The same would apply for decreases in small market capitalisation companies as well. As an example, ADW average market capitalisation as at 1 July 2009 and 1 July 2010 had diminished by 79% and 80%, respectively.

Figure 13 shows that the blue chip companies, such as SAB, BIL and AGL showed the most notable increase in average market capitalisation in terms of absolute figures. When comparing 2 July 2005 - 1 July 2006 to 2 July 2006 - 1 July 2007, the average market capitalisation of AGL and BIL increased by approximately R210 billion and R100 billion each, respectively. However, during the onset of the GFC, each of these companies saw their average market capitalisation diminish by R410 billion and R240 billion each, when comparing 2 July 2007 - 1 July 2008 to 2 July 2008 - 1 July 2009. SAB also saw a large leap in its market capitalisation during 2 July 2012 - 1 July 2011, when it rose by roughly R217 billion compared to the previous July-to-July year.

Figure 14 examines the average daily market capitalisation for the data sample. The overall trend is increasing, but Figure 14 shows that a dip was evident from May 2008 to May 2010, which overlapped the GFC period. These average market capitalisation figures only really started picking up in 2012 and have continued their increasing trend throughout 2013, as seen in Figure 14 and Figure 15 which examine the average annual market capitalisation for the data sample.

The standard deviation of the average annual market capitalisation, in Table 9, appears much greater during 2 July 2007 - 1 July 2008 and then again during 2 July 2012 - 1 July 2013. The averages shown in Table 9 for each July-to-July year group also vary greatly, with only some groups showing similar average figures.

Table 9: Summary Results for Average Annual Market Capitalisation

Groups	Count	Sum	Average	Standard Deviation
2 July 2005 - 1 July 2006	91	R 2 270 575 707 401	R 24 951 381 400	R 51 541 750 967
2 July 2006 - 1 July 2007	91	R 3 165 773 477 620	R 34 788 719 534	R 76 786 962 163
2 July 2007 - 1 July 2008	91	R 3 770 018 129 284	R 41 428 770 651	R 98 767 381 151
2 July 2008 - 1 July 2009	91	R 2 800 900 610 276	R 30 779 127 585	R 68 713 124 406
2 July 2009 - 1 July 2010	91	R 3 304 209 149 261	R 36 309 990 651	R 80 562 979 510
2 July 2010 - 1 July 2011	91	R 3 747 436 555 956	R 41 180 621 494	R 90 561 010 578
2 July 2011 - 1 July 2012	91	R 3 915 963 385 356	R 43 032 564 674	R 91 557 284 117
2 July 2012 - 1 July 2013	91	R 4 495 053 515 030	R 49 396 192 473	R 108 305 255 674

A one-way ANOVA exercise is again done for average annual market capitalisation. The same null hypothesis is applicable, namely that the average annual market capitalisation for each July-to-July year is the same. Thus, the suggestion is that the trading engine upgrade has had little effect on the average annual market capitalisation between each July-to-July group.

Table 10: ANOVA Results for Average Annual Market Capitalisation

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	37 499 290 584 389 900 000 000	7	5 357 041 512 055 700 000 000	0.741	0.647	2.022
Within Groups	5 205 036 031 382 740 000 000 000	720	7 229 216 710 253 810 000 000			
Total	5 242 535 321 967 130 000 000 000	727				

The p-value (0.647) in the results Table 10 is greater than 0.05 and hence we fail to reject the null hypothesis as the p-value is not statistically significant at the 0.05 level. It can therefore be suggested that the average annual market capitalisation between the July-to-July groups is identical. The F-statistic of 0.741 is less than the F-critical value, thus we fail to reject the null hypothesis as the F-statistic is not deemed statistically significant at 0.05. With the evidence at hand, it can therefore be expressed that the implementation of the new trading engine in July 2012 did not influence the average annual market capitalisation between each

July-to-July year group and therefore did not influence liquidity either. Again, similarly to the ANOVA results for the ILLIQ ratio and average daily value traded, the ANOVA results for average market capitalisation seem to also infer that the share price increases was not because of the trading engine – but rather due to natural market forces of demand and supply.

Figure 12: YOY Average Market Capitalisation Growth per Ordinary Share (2 July 2007 - 1 July 2013)

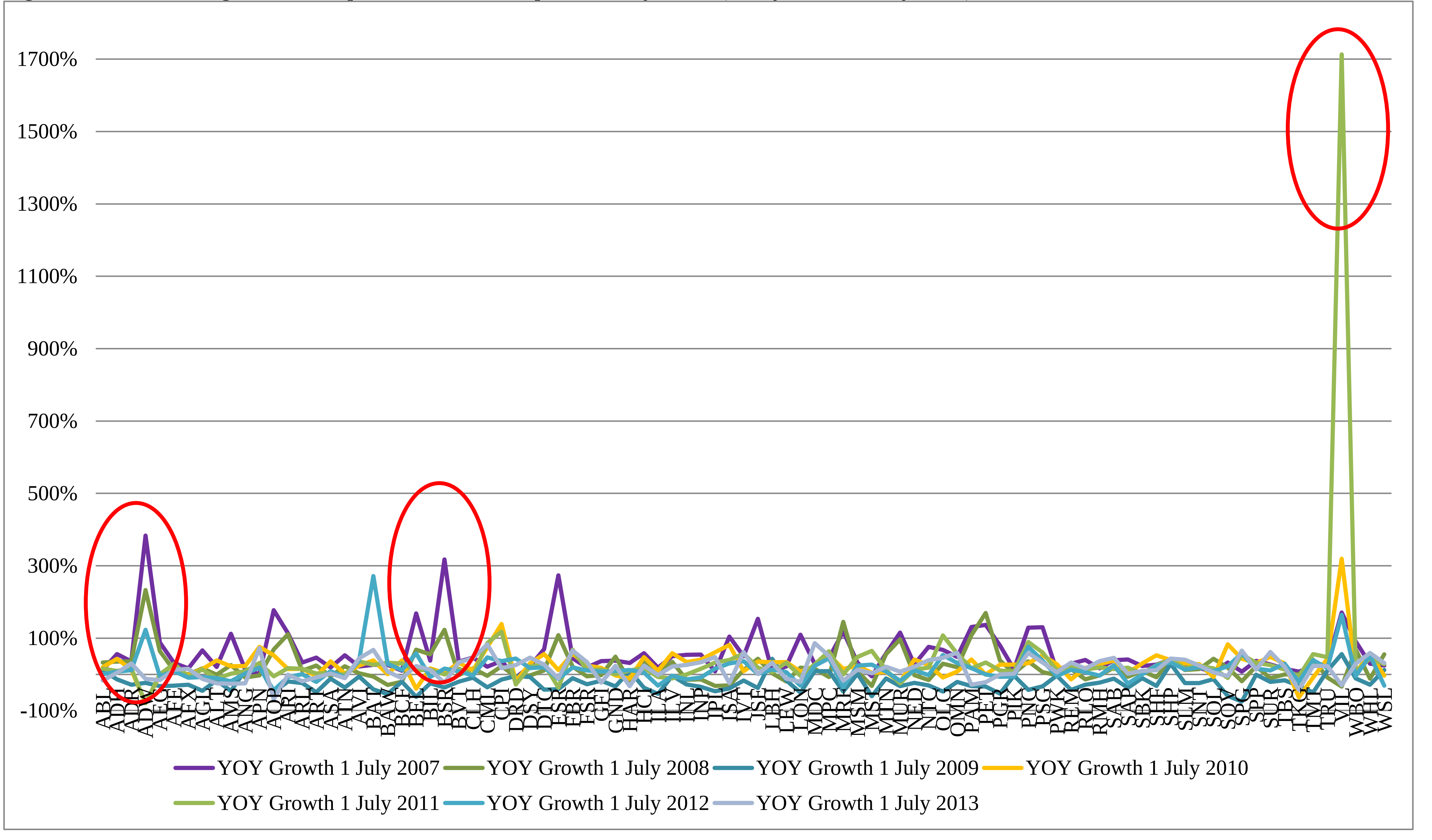


Figure 13: Average Market Capitalisation (2 July 2005 - 1 July 2013)

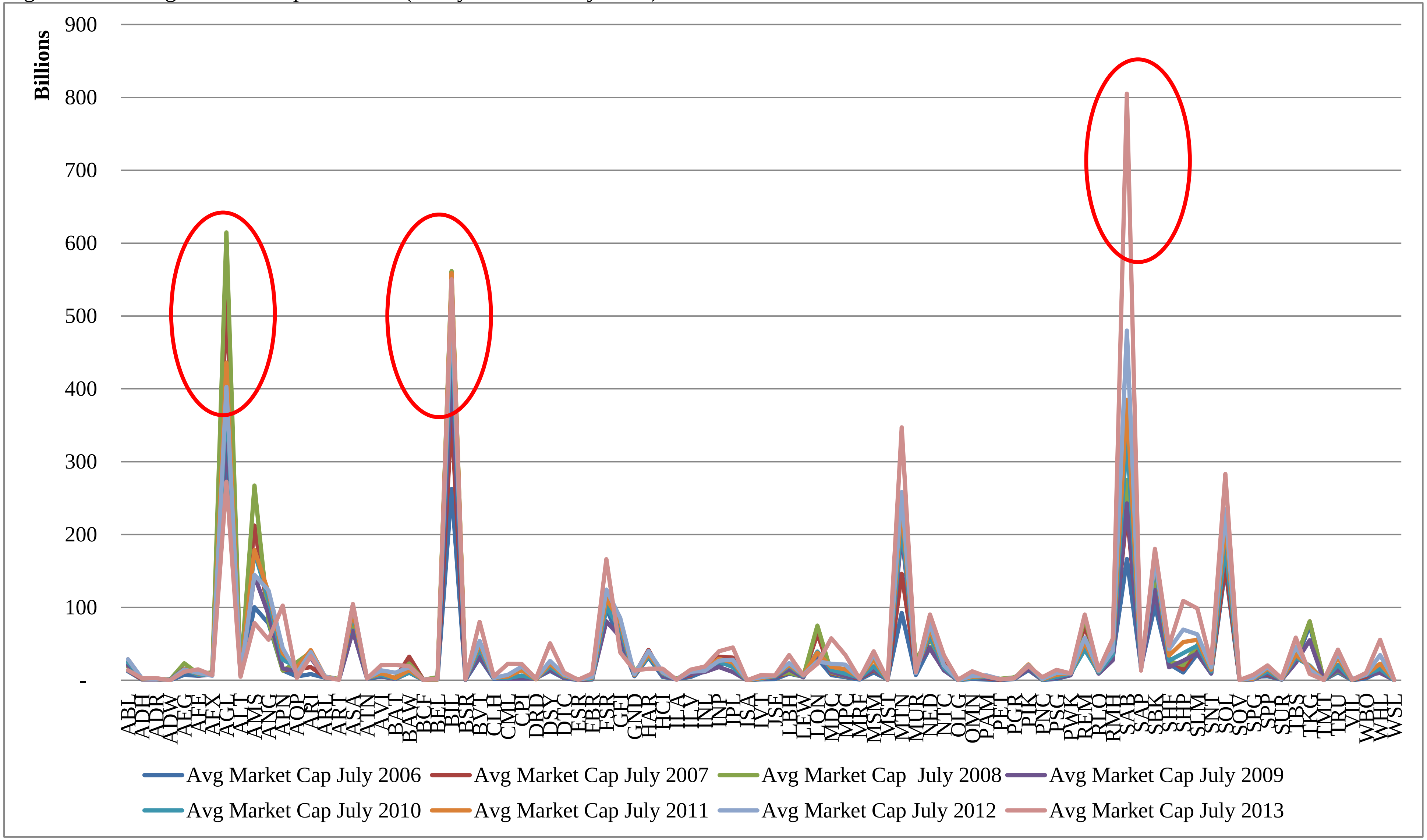
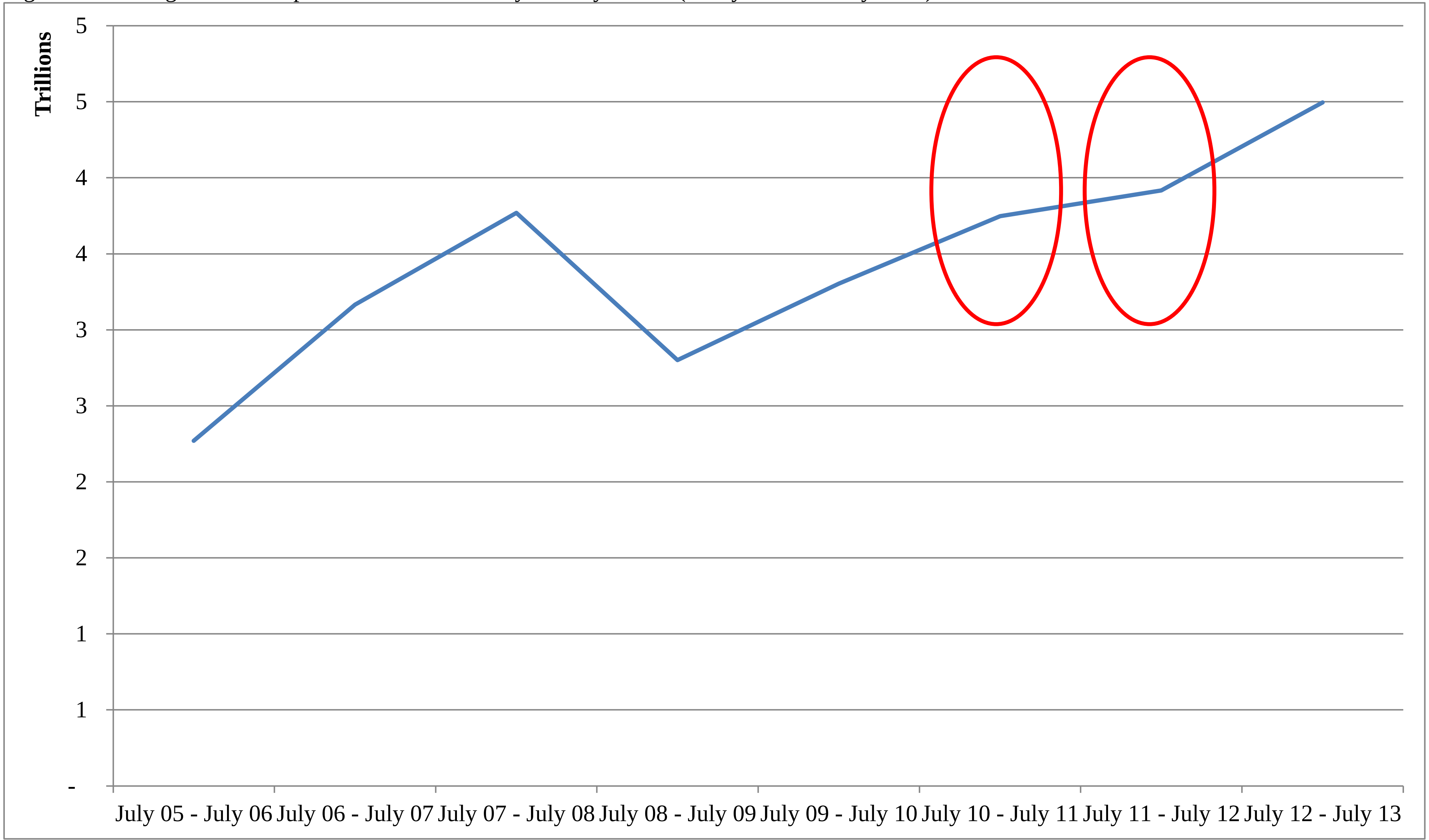


Figure 14: Daily Market Capitalisation (2 July 2005 - 1 July 2013)

Figure 15: Average Market Capitalisation for each July-on-July Period (2 July 2005 - 1 July 2013)



7.1.1.5 Average Spread

Unfortunately, due to data limitations the average spread data is only available from April 2007 and therefore creates a slight challenge regarding the comparison of the various liquidity measurements during the same data sample period. The average spread formula is shown in Equation 2 below.

Equation 2: Average Spread

$$AverageSpread = \frac{\sum(BestOffer - BestBid)}{n}$$

$$AverageSpread = \frac{\sum(Sum\ OfOfferPrice - SumOfBidPrice)}{\sum CountOfTotalUpdates}$$

- *SumOfBidPrice*
  - *Sum of the price of the best bid updates on the statistic date.*
- *SumOfOfferPrice*
  - *Sum of the price of the best offer updates on the statistic date.*
- *CountOfTotalUpdates*
  - *Count of the best bid and best offer updates on the statistic date.*

Figure 16 shows how the year-on-year growth of the annual average spread has changed during the data sample period. Super Group Ltd (SPG) (shown in the red circle) seems to show the most erratic year-on-year growth of a company’s annual average spread. Its annual average spread decreased by 84% during 2 July 2009 - 1 July 2010, increased by 319% during 2 July 2011 - 1 July 2012 and then finally by 115% during 2 July 2012 - 1 July 2013. Liberty Holdings (LBH) (shown in the red circle) was another ordinary share that showed a spike with regard to its year-on-year growth of its annual average spread. Both of these shares fall within the ZA02 trading segment and therefore typically have medium levels of liquidity.

Figure 17 shows the annual average spread per ordinary share within the data sample from 2 July 2007 -1 July 2013. When considering the annual average spread in absolute terms, Figure 17 shows that Liberty Ltd Group (LBH) and Palamin Palabora Mining Company Ltd (PAM) (shown in red circles) show the largest annual average spreads, particularly during 2 July 2008 - 1 July 2009. LBH is a ZA02 share as is PAM. It is, however, noticeable that PAM’s annual average spread decreases significantly, starting from 2 July 2008 - 1 July 2009.

Figure 18 illustrates the daily average spread for the entire data sample. The red circle shows how erratic daily average spreads were during the period that overlapped the GFC, namely July 2008 - January 2009. The daily average spread started to narrow following this volatile period, evident by the much smoother 22-day moving average trend that followed.

During 2 July 2007 - 1 July 2008, the annual average spread for the entire data sample was at roughly 60 cents (in the red circle) and decreased steadily over the data sample period to roughly 30 cents (in red circled) as can be seen in Figure 19. The volatility around the annual average spread also diminished significantly since the 2 July 2008 - 1 July 2009 period, shown in Table 11. It would appear that especially during the GFC, the annual average spread and volatility were at their highest levels, as can be expected during periods of significant instability and uncertainty.

Table 11: Standard Deviation of Annual Average Spread (2 July 2005 - 1 July 2013)

	2 July 2007 - 1 July 2008	**2 July 2008 - 1 July 2009**	**2 July 2009 - 1 July 2010**	**2 July 2010 - 1 July 2011**	**2 July 2011 - 1 July 2012**	**2 July 2012 - 1 July 2013**
Standard Deviation	72.646	122.260	53.838	32.993	27.980	29.039

The averages shown in Table 12 for each July-to-July year group are particularly similar from 2 July 2010 - 1 July 2013, as are the standard deviation figures.

Table 12: Summary Results of Annual Average Spread

Groups	**Count**	**Sum**	**Average**	**Standard Deviation**
2 July 2007 - 1 July 2008	91	5206.794	57.218	72.646
2 July 2008 - 1 July 2009	91	5870.675	64.513	122.260
2 July 2009 - 1 July 2010	91	3736.059	41.056	53.838
2 July 2010 - 1 July 2011	91	2958.543	32.511	32.993
2 July 2011 - 1 July 2012	91	2844.200	31.255	27.980
2 July 2012 - 1 July 2013	90	2954.118	32.824	29.039

In completing a one-way ANOVA exercise for the annual average spreads for the data sample, it is possible to discern how similar or dissimilar the July-to-July groups are. The null hypothesis, namely that the annual average spread for each July-to-July year is the same, is again applicable. The same premise is applicable, namely that the trading engine upgrade has had little effect on the annual average spread between each July-to-July group.

Table 13: ANOVA Results for Annual Average Spread

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	92 704.653	5	18 540.931	4.299	0.001	2.231
Within Groups	2 324 595.174	539	4 312.793			
Total	2 417 299.827	544				

The p-value (0.001) in the results Table 13 is less than 0.05 and hence we can reject the null hypothesis as the p-value is statistically significant at the 0.05 level. This would suggest that the annual average spread between the July-to-July groups is not identical. The F-statistic of 4.299 is much greater than the F-critical value, thus we reject the null hypothesis as the F-statistic is deemed statistically significant at 0.05. With the evidence at hand it can therefore be inferred that the implementation of the new trading engine in July 2012 could have influenced the annual average spread between each July-to-July year group and therefore liquidity as well. A reason for this could be that even if the best bid or best offer prices remained fairly subdued, the influx of the number of best bid/offers was significant (again one could argue because the technology allowed quicker access and exit to/from the market place) and therefore lowered the annual average spread and improved liquidity.

Figure 16: YOY Growth of Annual Average Spread per Ordinary Share (2 July 2005 - 1 July 2013)

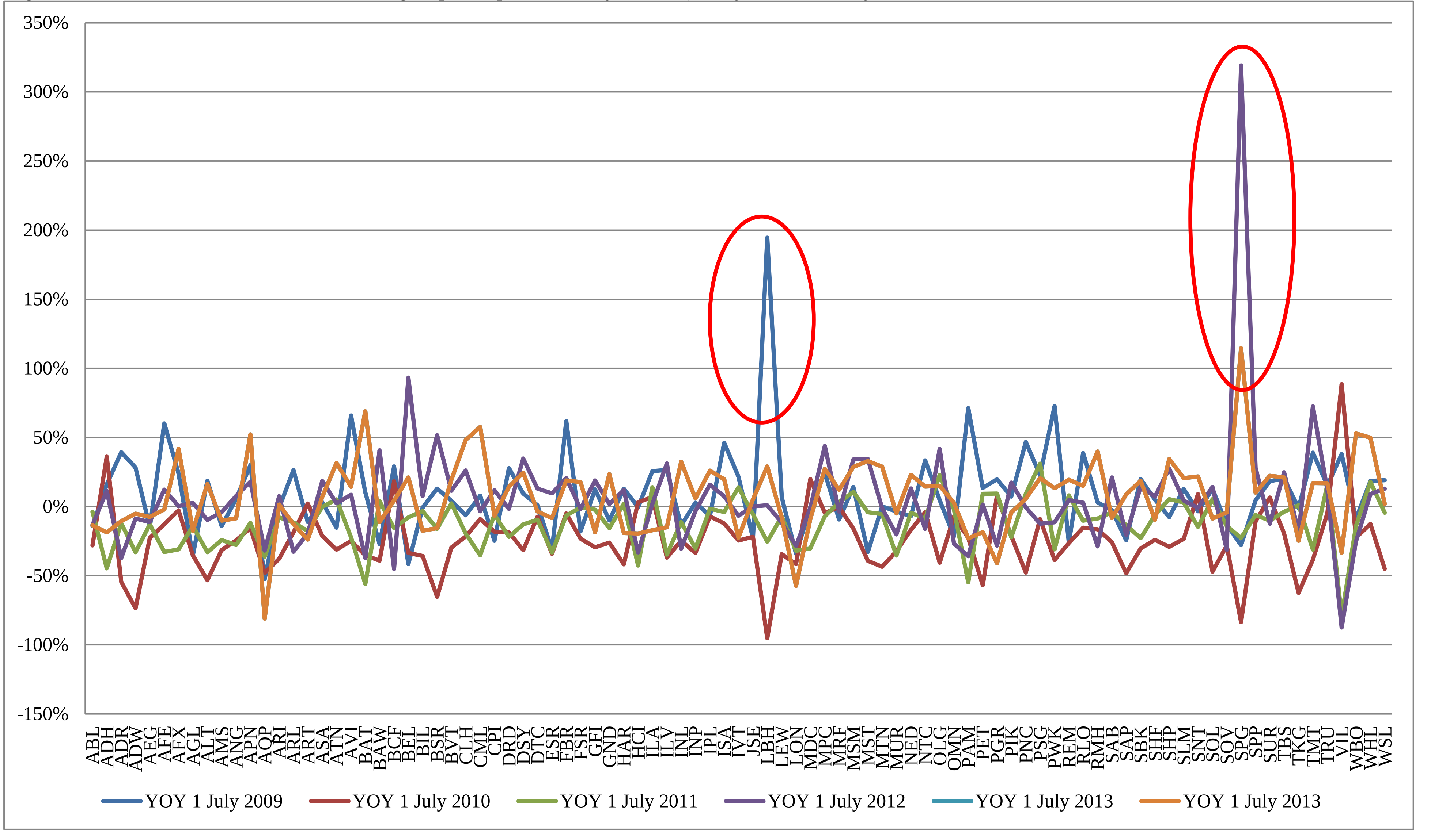


Figure 17: Annual Average Spread per Ordinary Share (2 July 2005 - 1 July 2013)

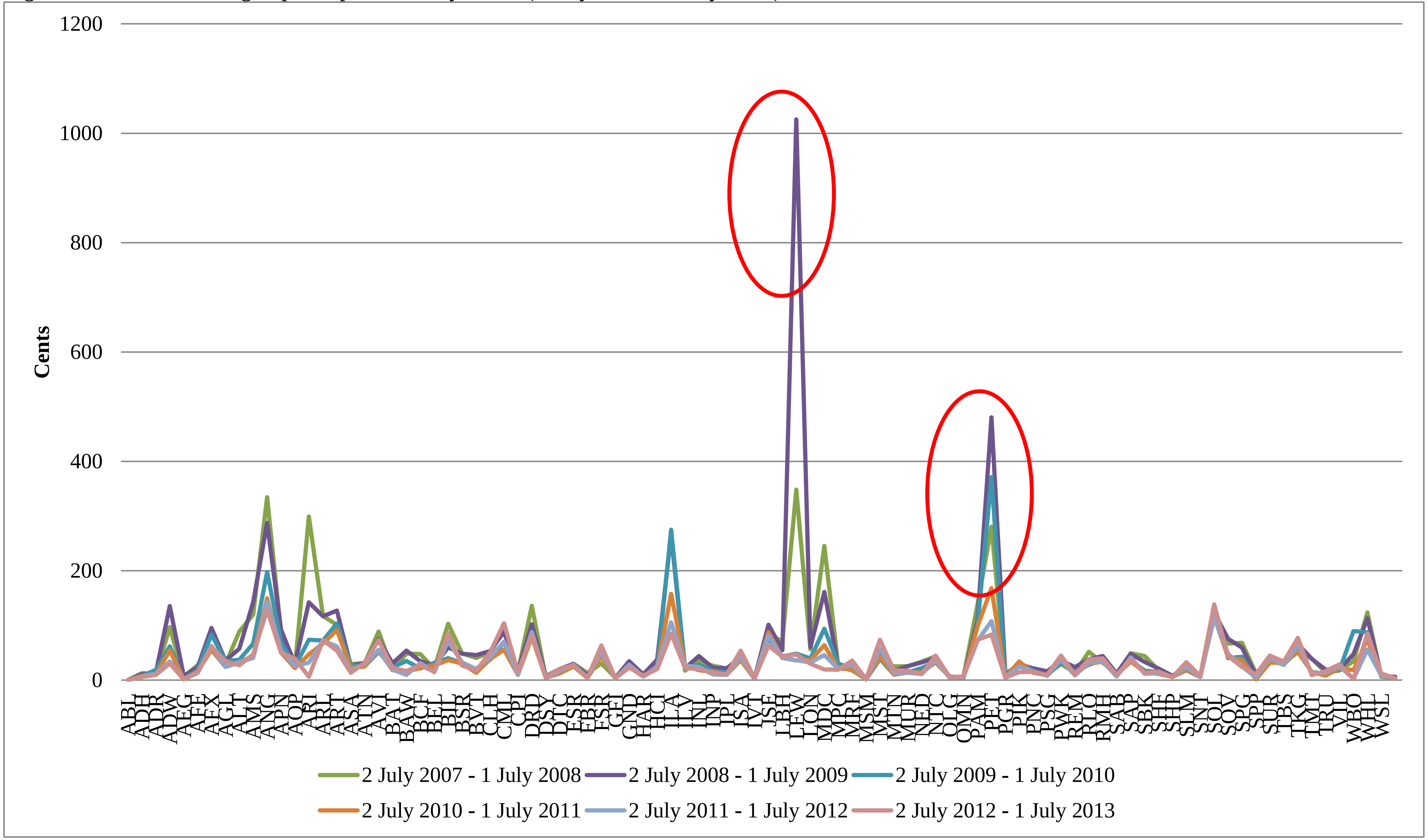


Figure 18: Daily Average Spread (2 July 2005 - 1 July 2013)

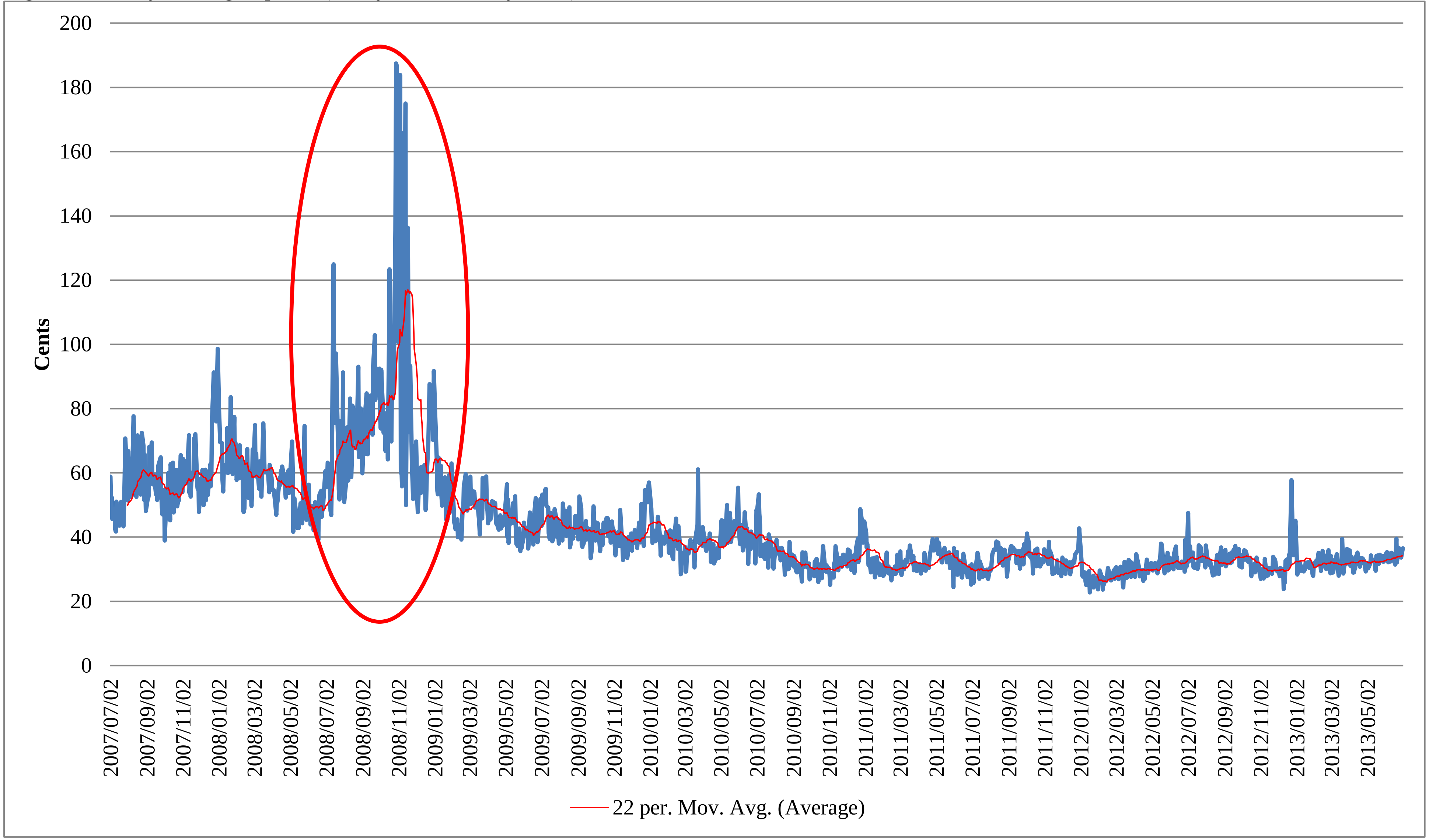
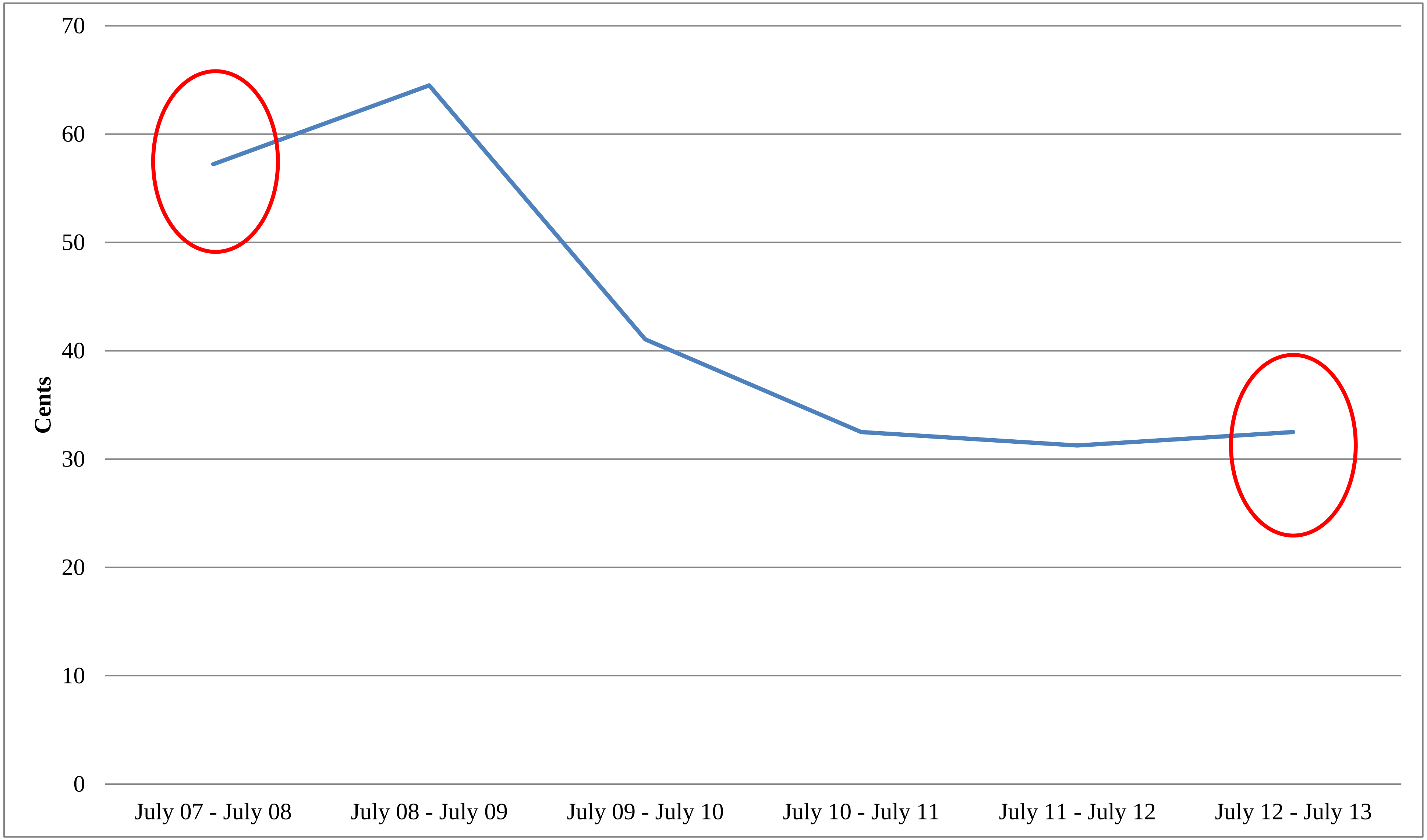


Figure 19: Annual Average Spread (2 July 2005 - 1 July 2013)



7.1.1.6 JSE Liquidity Measurement

The last liquidity measurement is one calculated by the JSE and represents annualised liquidity of the JSE central order book (COB) and ignores reported trades (off-order book trades), warrants and other investment products. It follows the WFE's turnover velocity formula shown below in Equation 3.

Equation 3: JSE Liquidity Measurement

$$JSE\ Liquidity\ Measurement = \frac{\underline{Monthly\ COB\ Domestic\ Share\ Turnover}}{Month\text{-}end\ Domestic\ Market\ Capitalisation} * 12$$

Due to some data discrepancies, the JSE liquidity measurement data for the period 2 July 2005 - 1 July 2006 was removed. Figure 20 shows that Imperial Holdings Limited (IPL) during 2 July 2007 - 1 July 2008, Telkom SA Limited (TKG) during 2 July 2008 - 1 July 2009 and ADW during 2 July 2009 - 1 July 2010, were the biggest outliers in terms of the JSE's liquidity measurement. Neither of these companies falls within the same trading segment as ADW is a ZA03 stock: TKG is a ZA02 stock and IPL forms part of the Top 40 stocks listed on the JSE. Thus, they do not share the same characteristics in terms of value traded, average spread or market capitalisation.

Figure 21 also shows that there has been a general decline in the annualised JSE liquidity measurement since 2 July 2007 - 1 July 2008 which then only really picked up from 2 July 2012 - 1 July 2013, the period in which the trading engine upgrade occurred.

The standard deviation of the annualised JSE liquidity measurement, in Table 14, appears rather large during 2 July 2009 - 1 July 2010, synonymous with the volatility experienced during the GFC period.

Table 14: Summary Results of Annualised JSE Liquidity Measurement

Groups	Count	Sum	Average	Standard Deviation
2 July 2006 - 1 July 2007	91	33.411	0.367	0.224
2 July 2007 - 1 July 2008	91	56.526	0.621	0.423
2 July 2008 - 1 July 2009	91	49.439	0.543	0.400
2 July 2009 - 1 July 2010	91	46.343	0.509	0.591
2 July 2010 - 1 July 2011	91	35.395	0.389	0.246
2 July 2011 - 1 July 2012	91	33.908	0.373	0.229
2 July 2012 - 1 July 2013	91	40.029	0.440	0.360

The one-way ANOVA exercise for the annualised JSE liquidity measurement for the data sample attempts to determine how alike or different the July-to-July groups are, regarding the average figures. Applying the same null hypothesis, that is, annualised JSE liquidity measurement for each July-to-July year is alike, is again relevant.

Table 15: ANOVA Results for Annualised JSE Liquidity Measurement

Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	5.185	6	0.864	6.167	0.000003	2.113
Within Groups	88.280	630	0.140			
Total	93.465	636				

The p-value (0.000003) in the results Table 15 is less than 0.05 and hence we can reject the null hypothesis as the p-value is statistically significant at the 0.05 level. This would suggest that the annualised JSE liquidity measurements between the July-to-July groups are not the same. The F-statistic of 6.167 is also much greater than the F-critical value, thus we can again reject the null hypothesis as the F-statistic is deemed statistically significant at 0.05. The results suggest that the introduction of the new trading engine in July 2012 could have affected the annualised JSE liquidity measurement each July-to-July year group and therefore liquidity as well. It would appear that once again, another volume based liquidity measurement responded positively to the introduction of the new trading engine. It can perhaps indirectly be inferred that improved technology has allowed much greater activity within the market, through the higher frequency that shares are being traded.

Figure 20: Annualised JSE Liquidity Measurement per Ordinary Share (2 July 2006 - 1 July 2013)

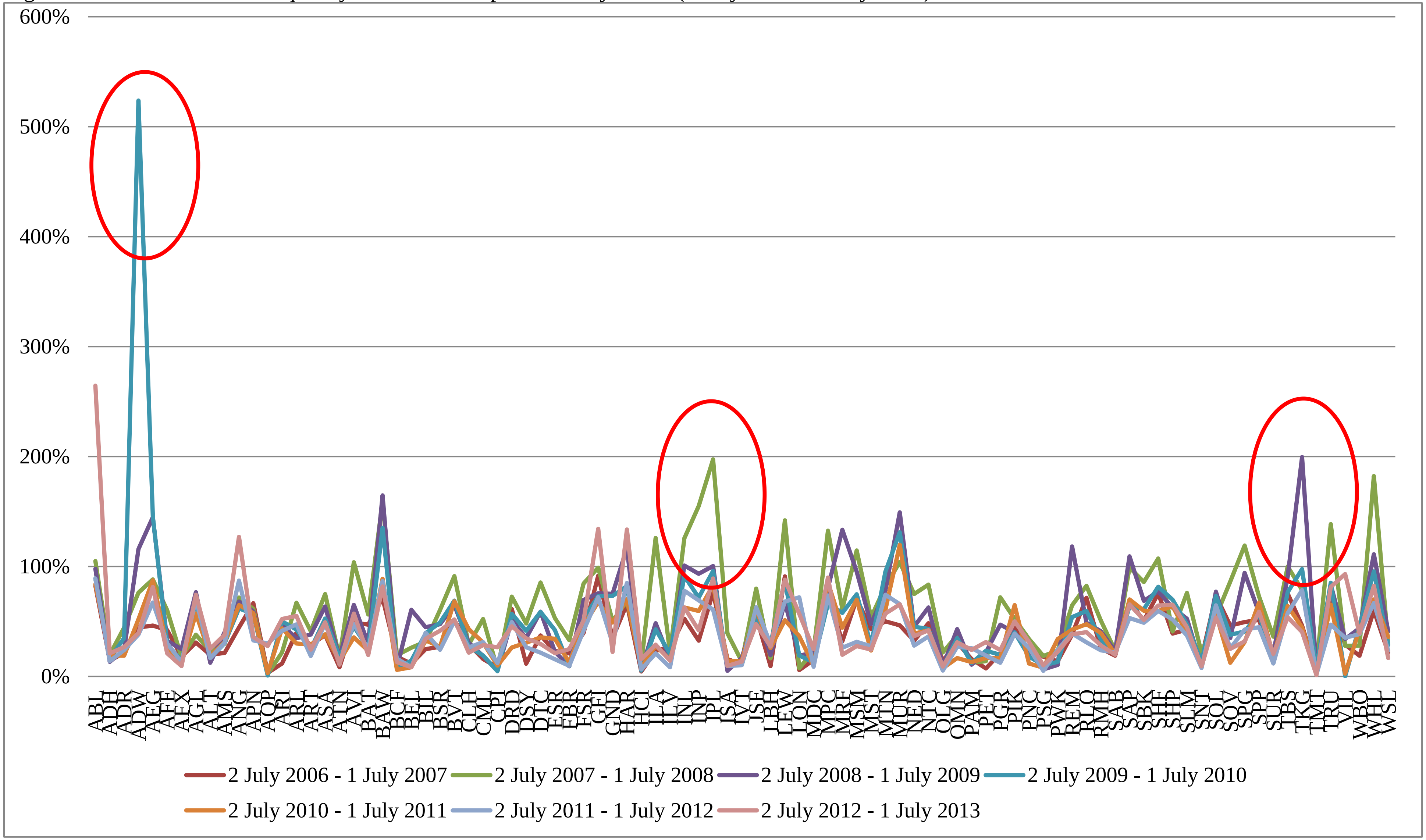
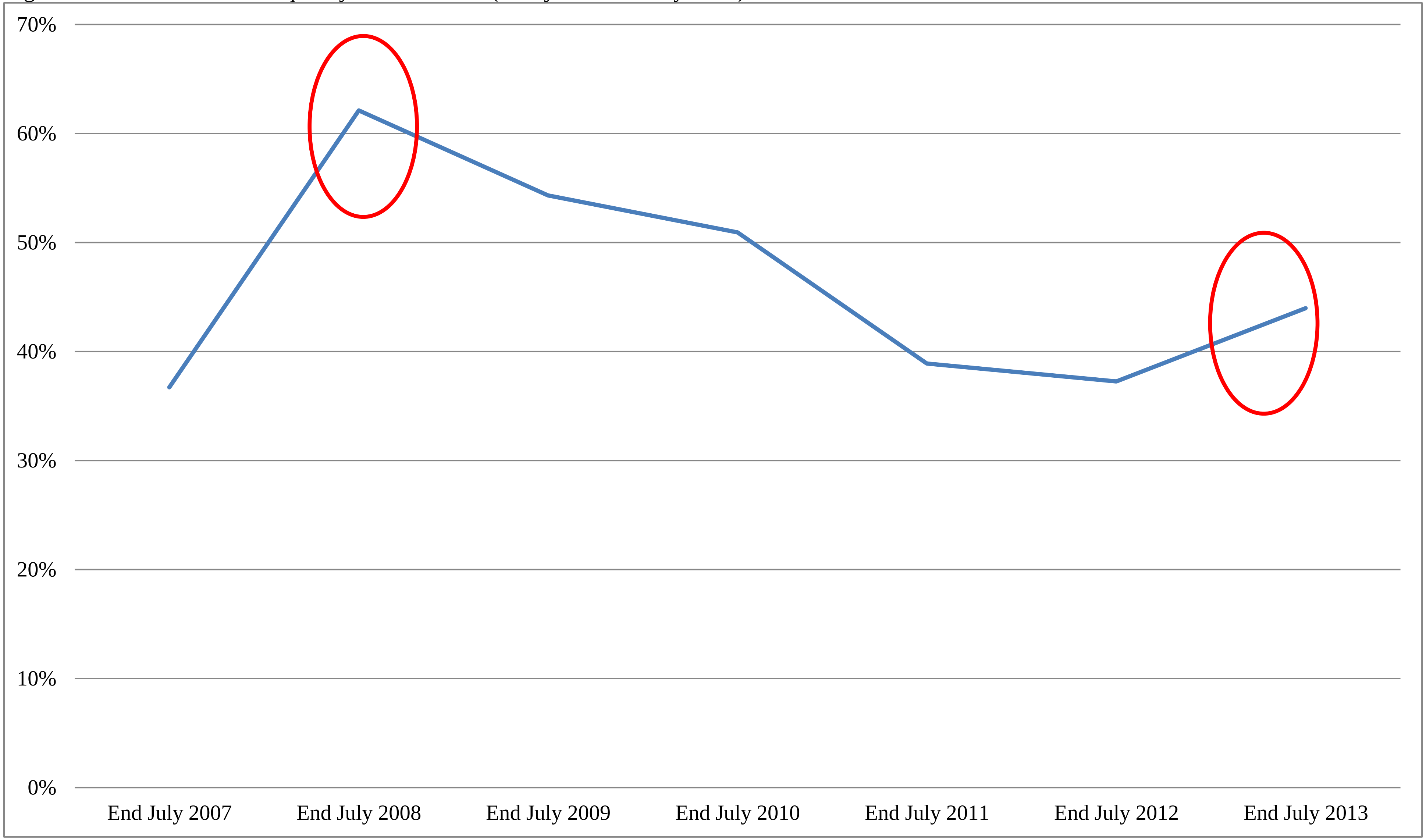


Figure 21: Annualised JSE Liquidity Measurement (2 July 2006 - 1 July 2013)



7.1.2 Correlations of Liquidity Measurement Rankings

The second part of the analysis examines to what degree these aforementioned liquidity measurements are correlated with each other in terms of each instrument's liquidity ranking.

Tables A to H in the appendices highlight how each instrument within the data sample ranked for each liquidity measurement where one equated to being the most liquid and 91, the least liquid. Because the ILLIQ ratio indicates illiquidity, a ranking of one indicates that the instrument is the least illiquid and therefore the most liquid. Table 16 below highlights the most liquid instruments per liquidity measurement for the entire data sample period. AGL and BIL appear to be the most liquid instruments as they are the most prevalent across most of the different liquidity measurements. What is significant is that these same instruments do not have the narrowest spread or the highest turnover ratios. The only liquidity measurements which appear to deliver roughly the same rankings include the ILLIQ ratio, average daily value traded and average market capitalisation.

Table 16: Most Liquid Instruments Based on Liquidity Measurement Rankings
(2 July 2005 - 1 July 2013)

	2 July 2005 - 1 July 2006	**2 July 2006 - 1 July 2007**	**2 July 2007 - 1 July 2008**	**2 July 2008 - 1 July 2009**	**2 July 2009 - 1 July 2010**	**2 July 2010 - 1 July 2011**	**2 July 2011 - 1 July 2012**	**2 July 2012 - 1 July 2013**
ILLIQ Ratio	AGL	AGL	AGL	MTN	ASA	AGL	AGL	SBK
Turnover Ratio	LEW	MSM	TRU	MUR	AEG	MUR	MPC	ABL
Average Spread	N/A	N/A	MRF	MRF	MRF	SPG	ADW	ADW
Average Daily Value Traded	AGL	AGL	AGL	AGL	AGL	AGL	AGL	MTN
Average Market Cap	AGL	AGL	AGL	BIL	BIL	BIL	BIL	SAB
JSE Liquidity Measurement	JSE	GFI	IPL	TKG	ADW	MUR	ABL	ABL

ASA – Absa Group Ltd SBK – Standard Bank Group Ltd LEW – Lewis Group Ltd MSM – Massmart Holdings Ltd TRU – Truworths International
MUR – Murray and Roberts Holdings AEG – Aveng Ltd MPC – Mr Price Group ABL – African Bank Ltd MRF – Merafe Resources SPG – Super Group Limited
GFI - Gold Fields Limited IPL – Imperial Holdings Ltd TKG – Telkom SA Limited

The liquidity measurement rankings for the data period are correlated against each other as seen in Tables I to P in the appendix section. It is evident that the ILLIQ ratio, average daily value traded and average market capitalisation rankings share a very strong and positive correlation with each other throughout the data sample period. The reason for this is perhaps because all three measurements involve some connection to share prices and their movements.

It is expected that a negative correlation would exist between the ILLIQ ratio and the turnover ratio – which is the case during 2 July 2005 - 1 July 2006; however the subsequent periods all seem to show a positive correlation between the rankings of the ILLIQ ratio and the turnover ratio.

Another significant observation is that correlation of the average spread rankings to the average market capitalisation rankings is negative throughout the data sample period. This suggests that though closing share prices might have increased the number of best bids and best offers were significant enough to warrant a decrease in average spread. In addition, the correlation of the average daily valued traded rankings to the average spread rankings is largely negative, though during 2 July 2009 - 1 July 2010, the correlation was positive and closer to zero.

The JSE liquidity measurement, however, shows a much wider range of the most liquid instruments during the data sample period. All of which differ from the most liquid instruments as identified by the ILLIQ ratio, average daily value traded and average market capitalisation.

Naturally, all these measurements involve different variables which influence it, therefore if would be difficult to assume that the same instrument would be ranked as the most liquid instrument for each measurement under review. If this was the case it would mean that the most liquid instrument, that fits this expression across all the different liquidity measurements, would have small share price returns (ILLIQ ratio), large volumes of its shares being traded relative to the shares available (turnover ratio), have small average spreads, large average daily value traded amounts and either have a large market cap because of a large share price increase or an increased number of shares in issue. Again, as Liu (2006) stated, liquidity is multidimensional and a great deal more complex than one would suppose.

7.1.3 Portfolio Event Study

The third part of the data analysis includes a portfolio event study to ascertain whether or not the introduction of the new trading engine (the event) on 2 July 2012 resulted in abnormal returns which were statistically significant. These abnormal returns, as a result of changes in closing prices, would naturally impact the calculation of market capitalisation. Thus, in determining whether market capitalisation (a liquidity measurement) increase during the trading engine upgrade was statistically significant, one could deduce that the trading engine upgrade did indeed affect liquidity.

The data sample period is dissected into three key time frames:

a) The estimation window (control period): 1 July 2011 - 28 June 2012
b) The event window: 29 June 2012 - 3 July 2012
c) The post-event window: 4 July 2012 - 1 July 2013

The data sample is also broken up into three key portfolios, each consisting of either ZA01 stocks, ZA02 or ZA03 stocks. ZA01 consists of the Top 40 stocks listed on the JSE and are also seen as the most liquid. ZA02 and ZA03 stocks have medium and low liquidity levels, respectively.

Using a regression of each of these portfolios' average daily returns to the market index (All Share), during the estimation window, it is possible to measure the impact of the event on each of the aforementioned portfolios' returns in the event window. The market model portfolio is shown as follows:

Equation 4: Portfolio's Return

$$r_{it} = \alpha_i + \beta_i r_{Mt}$$

r_{it} and r_{Mt} represent the portfolios' return and the All Share return on a daily basis, respectively. The intercept α_i and slope β_i are determined by running an OLS regression during the estimation window (Benninga, 2008). The abnormal return is calculated by deducting each portfolio's daily expected return from its actual return, during the event window. The abnormal return serves as a means of determining what impact the event (in this case, the trading engine upgrade) had on the market value of each of the portfolios (Benninga, 2008) and therefore its liquidity.

The test statistic for the daily abnormal return for each portfolio is calculated by dividing the average daily abnormal return of each portfolio by the standard error (Benninga, 2008). In assuming that the regression residuals are normally distributed, when the absolute value of the test statistic is greater than 1.96, one can ascertain that each portfolio's average daily abnormal return is statistically significant at the 95% level.

a) ZA01 Portfolio

Table 17: ZA01 Portfolio Estimation Window Output

Estimation Window	
Intercept	0.0100181
Slope	27.691417
R Squared	0.9400788
Standard Error	0.0766359

The R-squared shows that 94% of this portfolio's returns can be explained by the All Share Index. The slope is much greater than one, indicating that this portfolio's returns are a great deal more volatile than the market's returns.

Table 18: ZA01 Portfolio Estimation Event Window Output

Event Window							
Date	**Actual Return**	**Expected Return**	**Abnormal Return**	**Cumulative Abnormal Return**	**Abnormal Return Test**	**Statistically Significant**	**All Share Return**
2012/06/29	34.22%	38.96%	-4.73%	-4.73%	-0.62	No	1.37%
2012/07/02	-6.79%	-3.57%	-3.22%	-7.95%	-0.42	No	-0.17%
2012/07/03	32.49%	28.40%	4.08%	-3.87%	0.53	No	0.99%

On the day of the new trading engine implementation, the actual returns of portfolio ZA01 decreased with 6.79% and the market saw a drop of 0.17%. The abnormal returns of portfolio ZA01, based on the abnormal return test, during the event window are, however, not statistically significant, it cannot be conclusively interpreted that the trading engine implementation had an impact on the liquidity of portfolio ZA01. It could be inferred, that because ZA01 includes the most liquid stocks on the JSE already, their share price movements would not be significant seeing as their share prices are regularly updated in the market and do not reflect stale share price information.

b) ZA02 Portfolio

Table 19: ZA02 Portfolio Estimation Window Output

Estimation Window	
Intercept	0.0467798
Slope	17.787882
R Squared	0.0974895
Standard Error	0.5932678

Table 20: ZA02 Portfolio Event Window Output

Event Window							
Date	**Actual Return**	**Expected Return**	**Abnormal Return**	**Cumulative Abnormal Return**	**Abnormal Return Test**	**Statistically Significant**	**All Share Return**
2012/06/29	47.78%	29.06%	18.73%	18.73%	0.32	No	1.37%
2012/07/02	-141.55%	1.74%	-143.30%	-124.57%	-2.42	Yes	-0.17%
2012/07/03	29.85%	22.28%	7.57%	-117.00%	0.13	No	0.99%

Similarly, the ZA02 portfolio's abnormal returns were not statistically significant during the event window, with the exception of the day that the trading engine upgrade occurred. Abnormal returns for this portfolio decreased by 143.30% and the absolute abnormal return test was greater than 1.96, suggesting that the trading engine upgrade could have had a meaningful impact on liquidity. This trading segment holds medium liquid instruments, suggesting that a change in share prices might be meaningful as these share prices are not regularly updated and can therefore initially reflect stale share price information.

c) ZA03 Portfolio

Table 21: ZA03 Portfolio Estimation Window Output

Estimation Window	
Intercept	0.0086789
Slope	2.5713675
R Squared	0.0401902
Standard Error	0.1377449

ZA03 portfolio abnormal returns were not statistically significant during the event window.

Table 22: ZA03 Portfolio Event Window Output

Event Window							
Date	**Actual Return**	**Expected Return**	**Abnormal Return**	**Cumulative Abnormal Return**	**Abnormal Return Test**	**Statistically Significant**	**All Share Return**
2012/06/29	-6.25%	0.01%	-6.26%	-6.26%	-0.77	No	1.37%
2012/07/02	0.00%	0.51%	-0.51%	-6.77%	-0.06	No	-0.17%
2012/07/03	6.67%	0.13%	6.53%	-0.24%	0.80	No	0.99%

In summary, neither of the portfolios showed abnormal returns that were statistically significant, with the exception of the ZA02 portfolio on the trading engine upgrade date. In general it seems to suggests that the implementation of the trading engine did not have an impact on the aforementioned portfolio's returns and thereby their liquidity levels. Some possible reasons for this include that market participants are particularly inelastic to technological changes as every day is considered "business as usual". Considering the event window at hand and the short time period, one can believe that the influence of the trading engine upgrade cannot be observed immediately within the short term. Instead, one has to perhaps believe that it is because of market participants' behavioural changes accompanied with superior technology that one can only truly observe the influence over a much longer time frame. The reason for this is that according to industry opinion, "pure" HFT has hardly featured in the South African market. One of the arguments for this is that, HFT players, being "players of speed" require their positions to be hedged instantly. This means that the spot market and its derivative market should have little to no latency between them. Currently, that is not the case in the JSE. It can be argued that only once the two markets are on par with each other's latency levels, will there be a long-term effect on liquidity because of HFT activity.

Market participants' behavioural changes include adopting different trading strategies, such as algorithmic trading or forms of low latency trading. Depending on the trading technology at hand, it can foster or discourage certain trading strategies. As mentioned, the JSE's introduction of improved trading technology would deliver a low latency advantage to market participants and with that attract HFT activity which would encourage trading volumes (Corporate Communications Consultants, 2011).

7.1.4 JSE "Computer Trading" and Liquidity

The fourth part of the analysis examines how increased orders, because of the advanced trading technology and because of new trading strategies (low latency trading and algorithmic trading), have impacted trading volumes and liquidity on the JSE Equity Market. Although difficult to prove, one has to concede, given the evidence provided by Brogaard (2010), that there might indeed be some logic to this reasoning.

Unfortunately, due to data limitations it is difficult for the JSE to ascertain which of the trading activity is low latency trading and which is algorithmic trading. Therefore, a number of key assumptions were made based on the orders data which helped to isolate "computer trading" which encompasses low latency trading and algorithmic trading. The key assumption is that a trader is perceived to be a low latency/algorithmic trader if they have submitted approximately 5000 orders per day (roughly 100 000 orders per month) and if the word "algo" formed part of the trader's TraderID. The trades, value traded, volume traded and total amount of orders (total per-trade activity) which includes deleted and amended orders, were examined.

Again, due to the data limitations at hand, it was only possible to extract data from April 2007. But for comparative purposes, the data period for this data sample is from July 2007 - 1 July 2013.

Figure 22 compares the total volume traded (or shares traded) and the total number of orders related to the JSE's "computer trading". It is worthwhile noting that during 2007 to roughly mid-2009, the correlation between total volume traded and total number of orders for "computer trading", was fairly aligned. However, the total number of "computer trading" orders increased steeply from 2010, yet the total volume traded slumped and remained relatively flat until July 2012. From July 2012 to July 2013, total volume traded started to see an uptake, once again subsequent to the trading engine upgrade.

Figure 23 examines the total "computer trading" orders versus the total "computer trading" trades, which appear to show a positive correlation between the these two elements. Since end June 2011, the number of "computer trading" orders has increased considerably, as can be seen in Figure 23 on the next page. Notable heights were reached in total "computer trading" orders and trades during July 2012 to June 2013.

Figure 22: Total Volume Traded vs. Total Computer Trading Orders (July 2007 - July 2013)

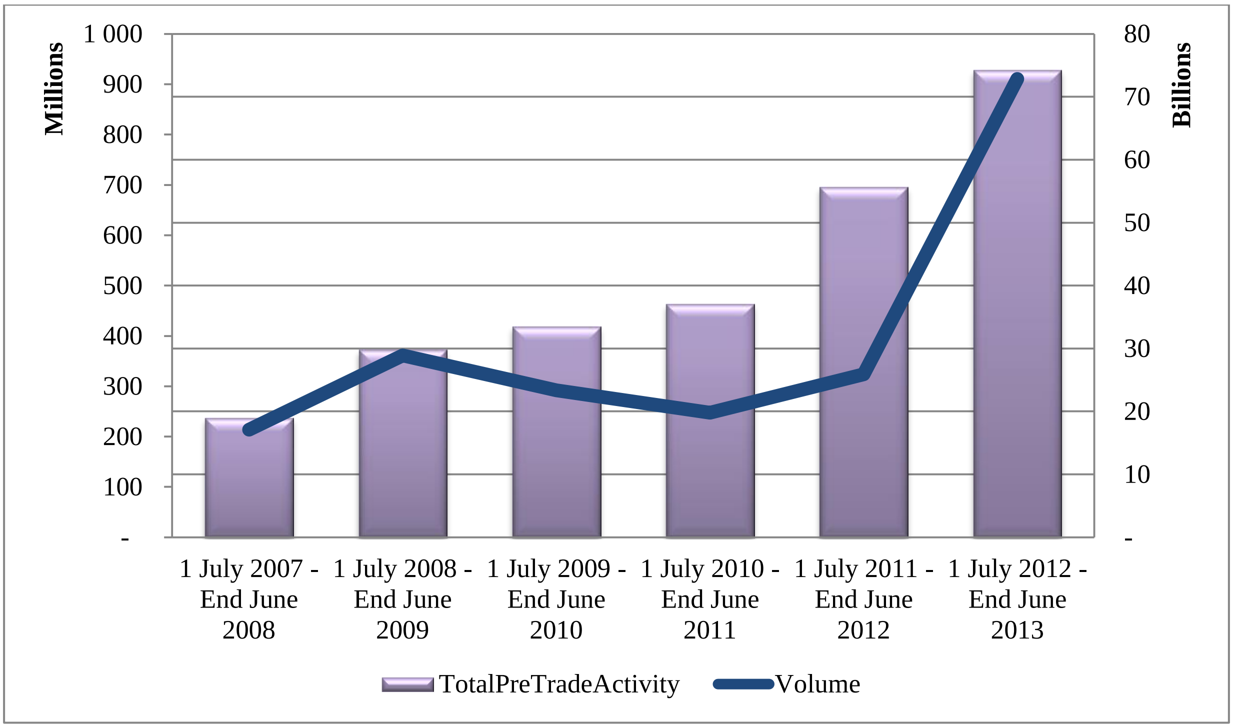
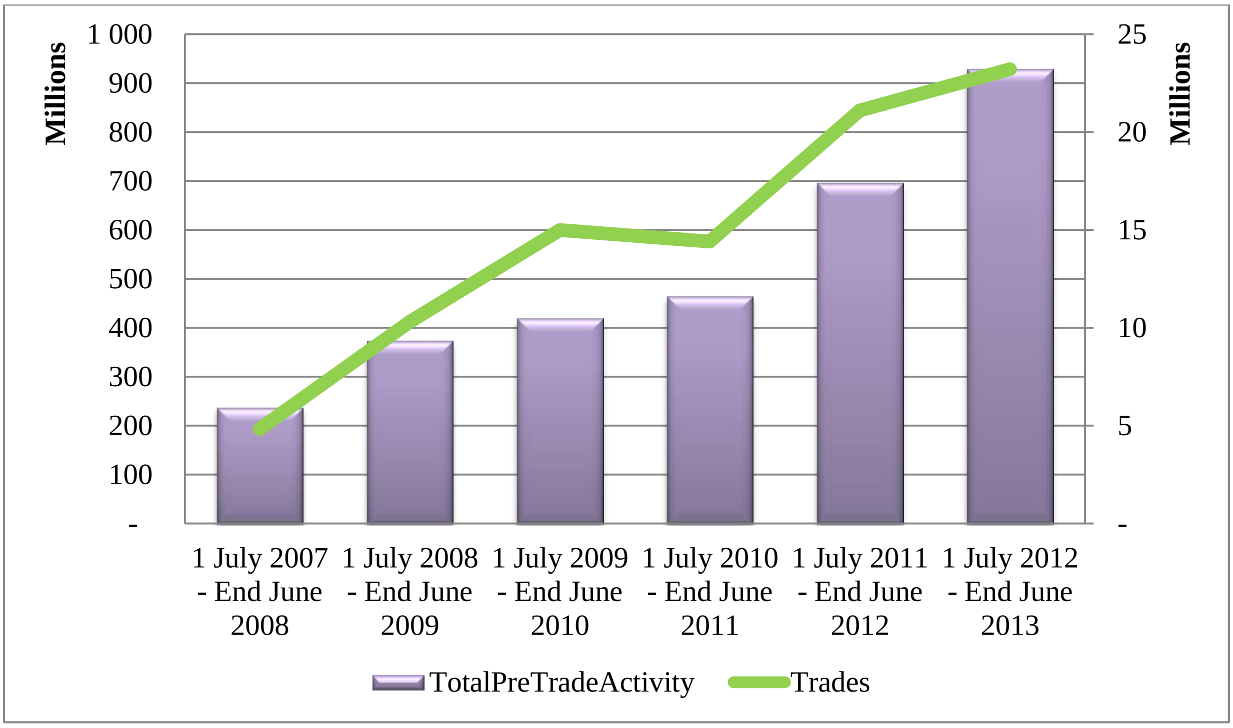
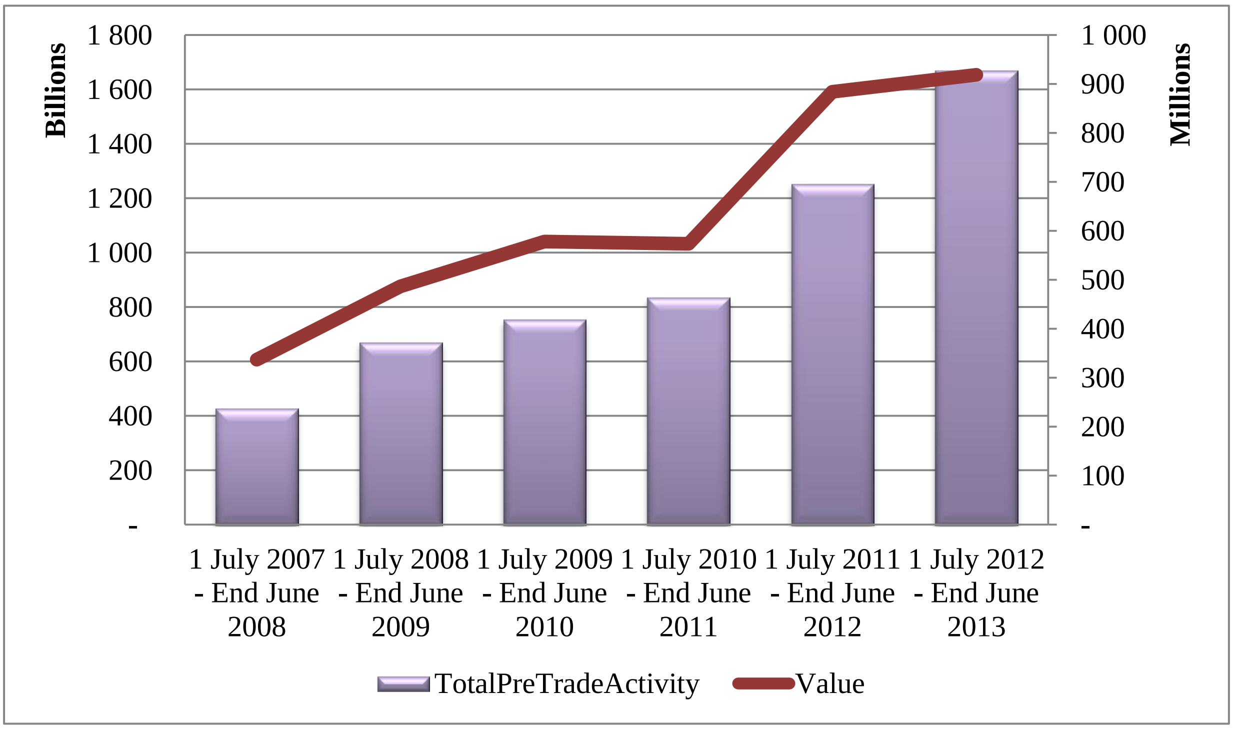


Figure 23: Total Trades vs. Total Computer Trading Orders (July 2007 - July 2013)



When comparing total "computer trading" orders with total "computer trading" value traded, there is again a very close correlation between the two variables, shown in Figure 24.

Figure 24: Total Value Traded vs. Total Computer Trading Orders (July 2007 - July 2013)

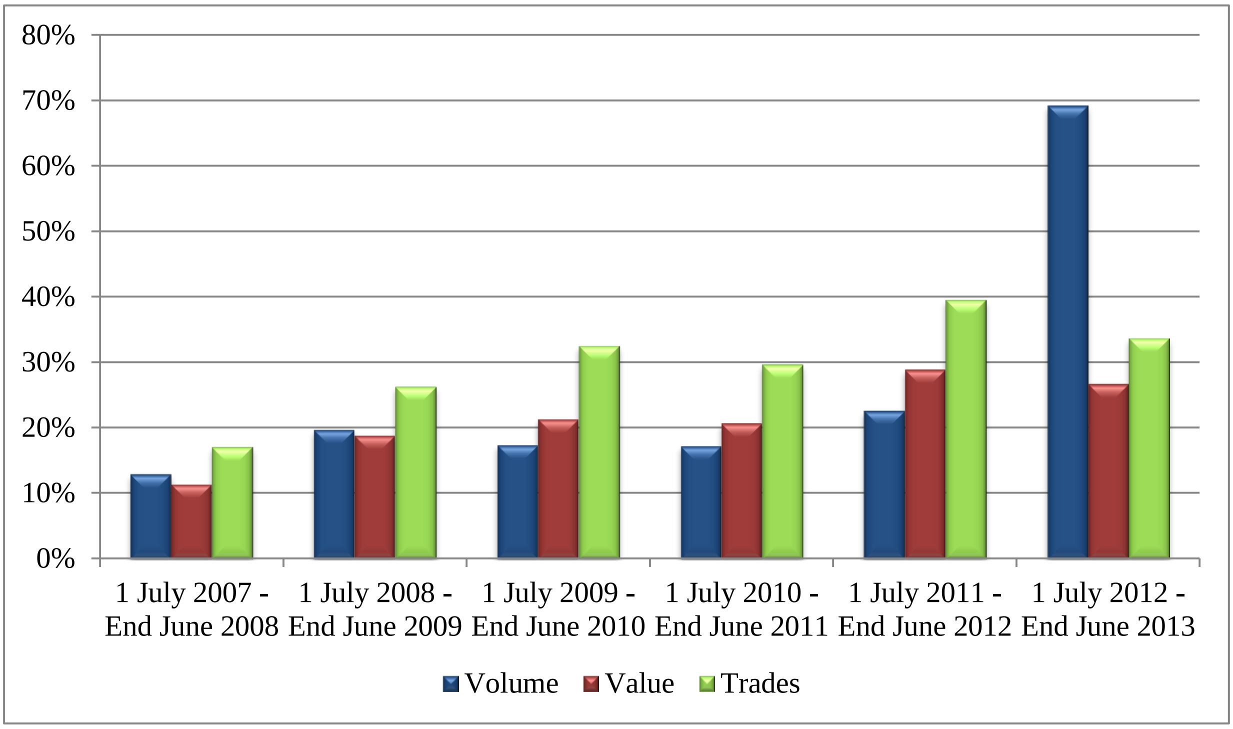


Overall, "computer trading" trades, value, volume and orders all increased since July 2007, with a notable peak during the period 1 July 2012 to end June 2013 when the second trading engine upgrade occurred.

In comparing this type of trading activity with all central order book activity, in Figure 25, it would appear that "computer trading" has seen an increasing trend, particularly from July 2011 to June 2013.

However, what do these variables say about liquidity and especially about the suggested positive relationship between the JSE's "computer trading", the trading engine upgrade and liquidity? Based on the research on hand, HFTs, or low latency traders would typically only trade instruments that already have high levels of liquidity so as to allow for the ease of entrance and exit from the market. This data sample includes 91 JSE listed instruments, with the Top 40 again representing the largest companies based on market capitalisation but which are also the most liquid shares listed on the exchange.

Figure 25: Computer Trading as Percentage of Central Order Book Trading
(July 2007 - July 2013)



Bearing this in mind, the danger exists that because the Top 40 shares make up a significant proportion of the total JSE trading activity, the results might be one-sided as it might indicate that very liquid instruments have now become more liquid but that the less liquid instruments' liquidity has not seen much improvement. To support this, a study by Hendershott, Jones and Menkveld (2011) examines the empirical relationship or connection between AT and liquidity. The authors use NYSE electronic message traffic (or orders), as a proxy for AT and find that as AT increases, so too does liquidity improve. Their findings show particularly that AT encourages liquidity especially for large-cap shares, as quote and effective spreads become narrower. Hendershott, Jones and Menkveld (2011) also find that AT did not only decrease adverse selection but also lowered the cost of trading and increased how informative quotes are.

The liquidity measurements that showed changes in liquidity that were statistical significant following the trading engine upgrade, namely the turnover ratio, average spread and the JSE's liquidity measurement, were compared with "computer trading" activity. Figure 26 on the following page shows that as total "computer trading" orders increased, the average turnover ratio decreased and only started picking up again from July 2012 to June 2013, during the trading engine upgrade. One could then perhaps indirectly suggest that as market conditions improved following the GFC and the trading engine upgrade in 2012, more shares were being traded (more transactions) as the increase in number of orders meant that there was a perceived increase in demand to buy and sell.

Figure 26: Average Turnover Ratio vs. Total Computer Trading Orders (July 2007-July2013)

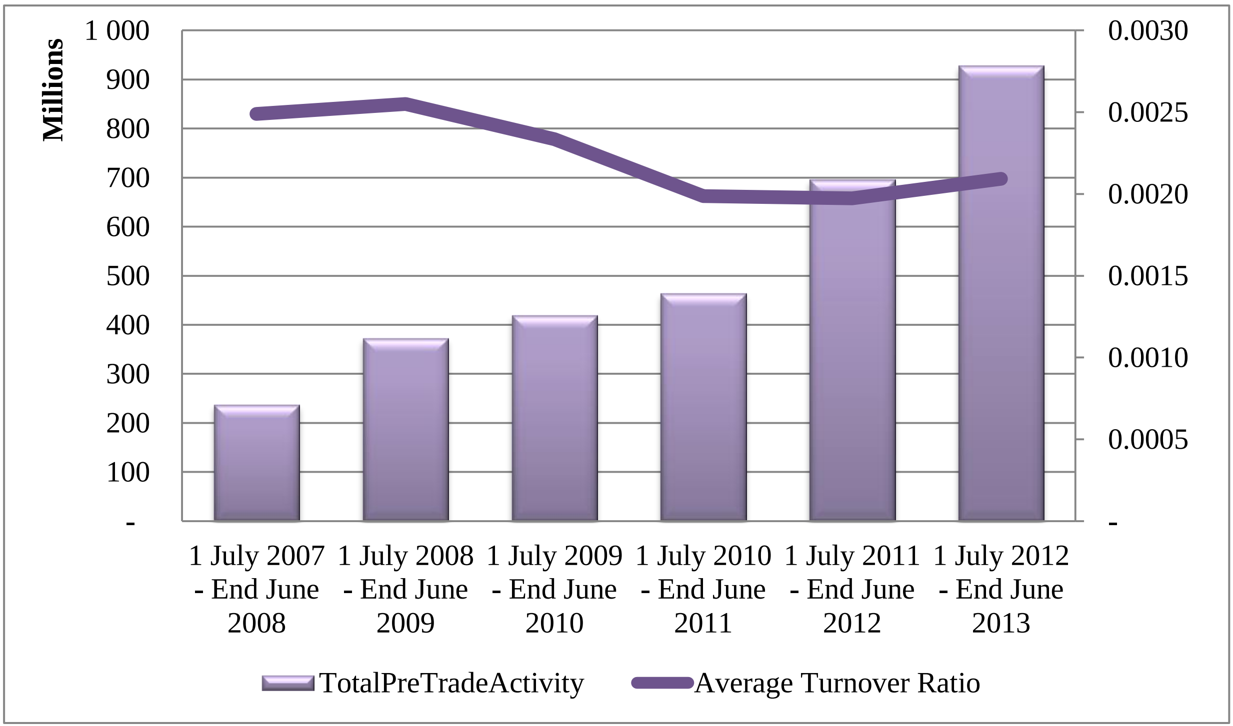
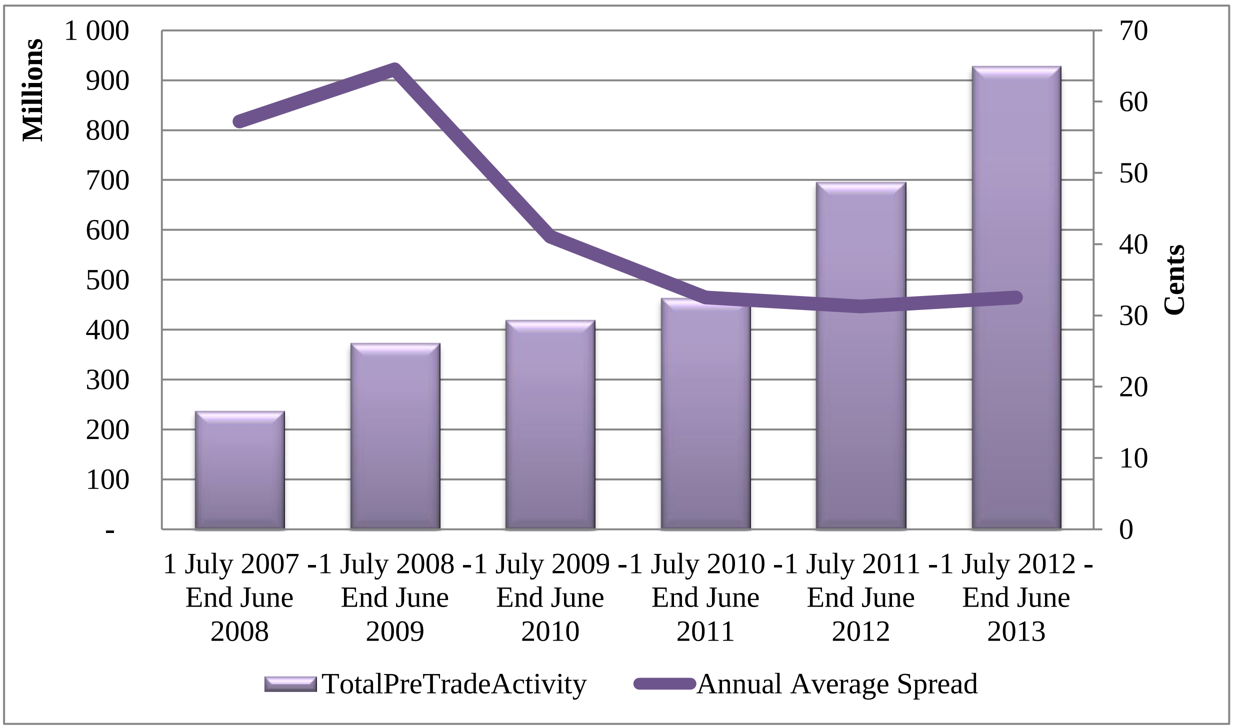
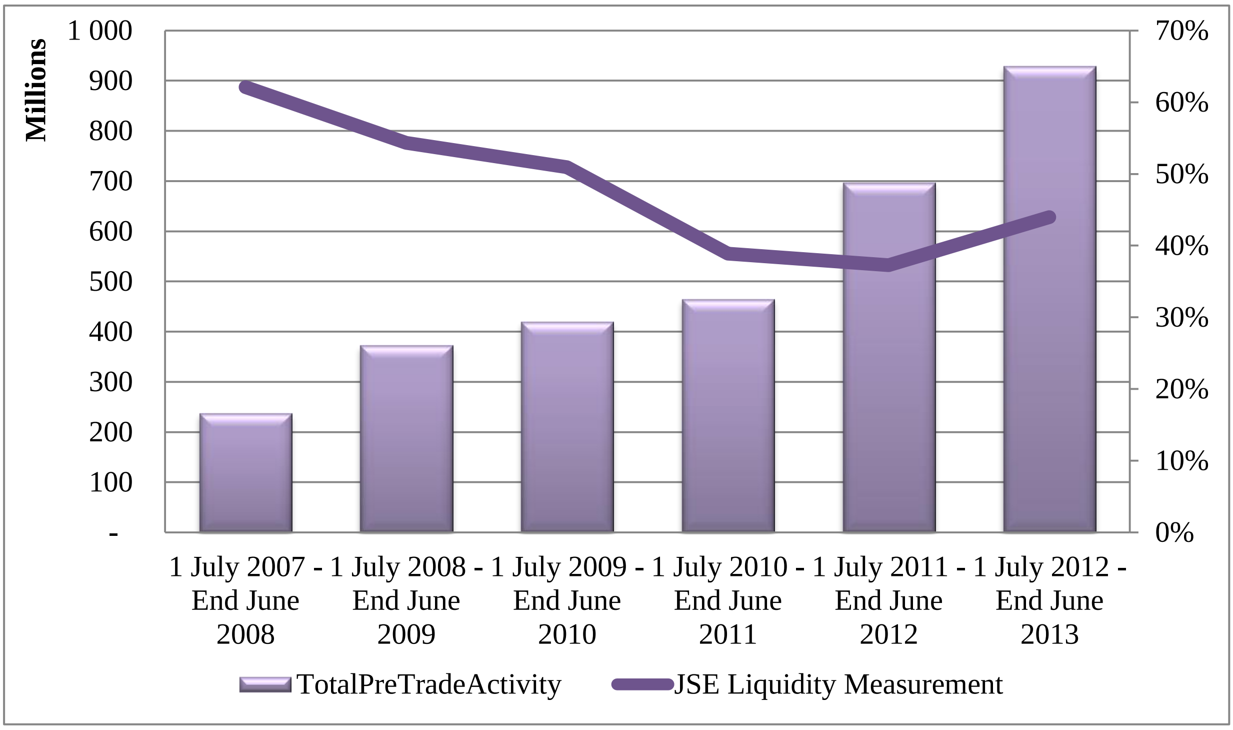


Figure 27: Annual Average Spread vs. Total Computer Trading Orders (July 2007- July2013)



When comparing the annual average spread to total "computer trading" orders (Figure 27), the annual average spread decreased significantly from July 2008 and then started to even out from July 2010 onwards. It can perhaps be inferred that the large inflow of best bid and best orders, because of "computer trading" had decreased the spread and therefore improved liquidity.

Figure 28: Average Annualised JSE Liquidity Measurement vs. Computer Trading Orders (July 2007 - July 2013)



According to Figure 28, liquidity within the JSE Equity Market decreased significantly from July 2007 until June 2012, and only from July 2012 did liquidity appear to increase again. During the same time "computer trading" orders started to increase gradually, as did "computer trading" trades and volume shown in Figure 25.

7.1.5 Summary of Analysis

The results of the various parts of the analysis are summarised as follows:

a) Liquidity Measurements Compared

Each of the liquidity measurements examined initially seemed to suggest that liquidity improved particularly during the 2 July 2012 - 1 July 2013 period. However, once ANOVA exercises were conducted for each measurement to ascertain whether the influence of the trading engine on liquidity was statistically significant, the results were less conclusive.

Table 23 summarises the outcome ANOVA exercises for each liquidity measurement:

Table 23: Summary of ANOVA Results for each Liquidity Measurement

Liquidity Measurement	**Statistically Significant**
ILLIQ Ratio	No
Turnover Ratio	Yes
Average Spread	Yes
Average Daily Value Traded	No
Average Market Capitalisation	No
JSE Liquidity Measurement	Yes

The shortcoming of the ANOVA exercise was that it was not possible to conclusively deduce the influence of the trading engine on liquidity for a particular July-on-July year group, that is, 2 July 2012 - 1 July 2013. Rather, reliance was placed on the inferences.

The ANOVA results for the ILLIQ ratio, average daily value traded and average market capitalisation – whose liquidity formulas are all connected to share price seemed to suggest that share price movements, due to demand and supply, and were not significant enough to suggest the influence of other external forces, such as a trading engine upgrade in this case.

The ANOVA results for the turnover ratio, average spread and the JSE's liquidity measurement all seemed to infer that an increase in volume/orders, brought on by the easier and quicker access that the trading engine was affording market participants, affected liquidity significantly. One could infer that the trading engine introduced low latency trading, encouraged order flow and therefore influenced liquidity positively. As previously mentioned when Hendershott, Jones and Menkveld (2011) had examined whether the increased AT improved market liquidity the authors found that the spreads of large NYSE stocks narrowed and that both adverse selection and trade-related price discovery reduced because of AT. Authors, Hasbrouck and Saar (2013) also stated that speed is vitally important to traders as it allows for the ultimate desire to create profitable opportunities by being the "quickest to market" i.e. low latency trading. The result has been that market players are continuously searching for state-of-the-art technology that would afford immediate access to the market place.

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b) Correlations of Liquidity Measurement Rankings

The second part of the analysis offered some insight into how different the outcomes of each of the liquidity measurements rankings were. Characteristics such as narrow spreads, large market capitalisation and high average daily value traded were not always synonymous with liquidity.

This is reinforced by the notion of how complex liquidity really is, as Liu (2006) and. Amihud, Mendelson and Pedersen (2005) had emphasised.

c) Portfolio Event Study

The third part of the analysis, following the realisation that liquidity measurements offered varying results in terms of liquidity and that the ANOVA exercise offered inconclusive results, was to determine whether the impact of the trading engine on liquidity (portfolio returns), through a portfolio event study, was statistically significant.

Although the returns of the ZA02 portfolio seemed to suggest that the trading engine upgrade did impact liquidity for this portfolio, overall the event study did not seem to share the same results for the ZA01 and ZA03 portfolios.

As expressed previously, the results could be explained because of market participants' immunity to technological changes. It is the actual market participant behaviour due to factors such as regulatory changes in markets, billing methodologies, clearing models and trading strategies that actually influence liquidity. Technology is just a means to access a market and instead it is the actual market behaviour that brings the technology to its full potential. As mentioned, the JSE Equity Market and JSE Equity Derivative Market does not share the same latency levels – as each of these markets use different trading technology and thus sit on different platforms as well. This disparity means that 'pure' HFT players will not seek to 'play' in this market as they cannot hedge their positions instantly.

d) JSE Computer Trading

Off the cuff it would appear that the trading engine upgrade which has encouraged increased "computer trading" orders have also led to an increase in liquidity, because of increased trading and volumes. All the elements such as increased market capitalisation, narrowed spreads, increased trading activity particularly during the 2 July 2012 - 1 July 2013 period seem to suggest that there is indeed a positive relationship. However, the results are not conclusive or statistically significant enough to prove an exact connection. Instead reliance is placed on the indirect associations and what the results infer.

8 CONCLUSION

The JSE Equity Market has evolved dramatically from an informal market conducted between chains 126 years ago, to a formidable force in being recognised as the most well regulated exchange in the world to sporting the ability for participants to execute in the JSE Equity Market central order book at speeds almost 400 times faster than the previous trading engine.

Growth in trading activity following each trading engine upgrade in the JSE Equity Market has been quite evident. The microstructure changes, such as low latency trading that came about because of the technological enhancement and the plethora of academic research concerning high speed trading and liquidity, posed the question as to whether there was a trend regarding the exchange's liquidity. It also posed the question as to whether all liquidity was the same and whether it truly was as multidimensional as some authors had suggested.

In examining a number of different liquidity measurements to ascertain whether there was indeed a positive change in liquidity following the trading engine upgrade, it appeared initially that there was indeed an influence. However, once ANOVA exercises were conducted for each measurement to ascertain whether the influence of the trading engine on liquidity was statistically significant, the results were less conclusive. The turnover ratio, average spread and the JSE liquidity measurement showed positive results, whilst the ILLIQ, average daily value traded and average market capitalisation showed the opposite. In fact, half of the liquidity measurements showed results that were statistically significant, whilst the other half did not. Instead reliance was made on the strength of the indirect associations and what the results inferred. The purpose of the ANOVA analysis is to predict a single independent variable (liquidity) on the basis of one or more predictor variables (in this instance, the trading engine upgrade). It is difficult to control for the multiple factors that can affect liquidity, therefore it is suggested that for the purposes of future research a regression model with control variables could be considered as the regression might be better at inferring causality – unlike the ANOVA exercise. In addition, a Chow Break test might also be worthy of conducting to ascertain any structural breaks in the data.

In addition, the commonality between the liquidity measurements' instrument rankings in terms of correlation was also weak. Characteristics such as narrow spreads, large market capitalisation and high average daily value traded were not consistently synonymous with liquidity.

The third part of the analysis focused on whether the impact of the trading engine on liquidity (portfolio returns), through a portfolio event study, was statistically significant. The results for portfolios ZA01 and ZA03 were not statistically significant, yet for portfolio ZA02 the results suggest that the trading engine did indeed have an influence on these medium liquid stocks.

The last part of the analysis indicated that the trading engine upgrade which has encouraged "computer trading" orders, also led to an increase in liquidity. As a possible extension to the study, it would be prudent to again consider a regression analysis for which there is control for the trading engine upgrade. Possible extensions of the research include determining the impact of technological enhancements on the JSE Equity Derivative Market, on JSE Equity Market liquidity levels. Currently the JSE Equity Market and JSE Equity Derivative Market each use a different trading technology and a different trading platform. The result is that each market does not share the same latency levels of the other. This inequality means that for market players that are heavily reliant on high speed trading and hedging, their risk exposure becomes too material and they will therefore search for other markets that meet their needs. One trading platform that offers the same trading technology for each market could contribute towards the exchange's desirability as liquid market place.

Apart from the technological, another avenue of research could include the effect of the introduction of a designated market making scheme and the resultant impact on JSE Equity Market liquidity. In unpacking the impact of frictions on a market's efficiency, it would also be useful to understand the resultant effect of the revised JSE Equity Market trading fee methodology on the JSE Equity Market liquidity levels, before and after the revision. Amihud, Mendelson and Pedersen (2005) indeed believe that need for a greater universe of stocks, market making structures and addressing trading related costs where needed, would enhance liquidity.

A final extension of the research would also include the liquidity effect of an increase in free float stock requirements of less liquid securities listed on the JSE Equity Market. The turnover ratio has shown positive results; therefore one could surmise that by making more tradable stock available, the effect on liquidity would be positive.

In summary, the results are not fully conclusive to show a positive relationship between the trading engine upgrade, low latency trading and liquidity. However, were market frictions limited or removed, the results might have been different and reflected a more liquid and efficient market. This said, a frictionless market is clearly not possible, the JSE Equity Market understands that by lessening the inhibiting factors, encouraging the development of a market that offers timely, cost effective and efficient execution services, liquidity will improve and the exchange will operate even more competitively.

9 REFERENCES

Amihud, Y. 2002. 'Illiquidity and Stock Returns: Cross-section and time-series effect'. *Journal of Financial Markets*. vol.5, no.1, pp. 31-56

Amihud, Y & Mendelson, H 1986. 'Asset Pricing and the Bid-Ask Spread'. *Journal of Financial Economics*, vol. 17, no. 2, pp.223-249

Amihud, Y, Mendelson, H & Lauterbach, B 1997. *Market Microstructure and Securities Values: Evidence from the Tel Aviv Stock Exchange*, Department of Finance, Working Paper Series FIN-98-004

Amihud Y, Mendelson, H & Pedersen, LH 2005, 'Liquidity and Asset Prices'. *Foundations and Trends in Finance*, vol. 1, no. 4, pp. 269-364

Benninga, S 2008, *Financial Modeling*, 3rd edn, Massachusetts Institute of Technology, United States of America.

Bernstein, PL 1987. 'Liquidity, Stock Markets, and Market Makers'. *Financial Management*, vol. 16, no. 2, pp. 54-62

Biais, B, Foucault T & Salanie, F 1998. 'Floors, dealer markets and limit order markets'. Journal of Financial Markets, vol. 1, no. 3-4, pp. 253-284

Breen, WJ, Hodrick, LS & Korajczyk, RA 2002. *Predicting Equity Liquidity'*, Institute for Operations Research and the Management Sciences (INFORMS), Management Science, vol. 48, no. 4, pp.470-483

Brogaard, JA. 2010. *High Frequency Trading and its Impact on Market Quality*. Ph.D. Northwestern University School of Law. Available at: http://qed.econ.queensu.ca/faculty/milne/870/SSRN-id1641387.pdf [Accessed 24 September 2013]

Chordia, T, Roll, R & Subrahmanyam, A 2001, 'Market Liquidity and Trading Activity'. *The Journal of Finance*, vol. 56, no. 2, pp. 501-530

Corporate Communications Consultants, 2011. *JSE's New Trading Platform to offer Faster Trading Capabilities.* [press release] 4 February 2011. Available at: http://www.jse.co.za/about-us/media/Press-Releases/Full-Story/11-02-

04/JSE_s_New_Trading_Platform_to_offer_Faster_Trading_Capabilities.aspx [Accessed 24 September 2013].

Cumming, D, Johan, S & Li, D 2011. ‘Exchange trading rules and stock market liquidity’. *Journal of Financial Economics,* vol. 99, no. 3, pp. 651-671

Deutsche Bank Research, 2011. *High-frequency trading: Better than its reputation?* Frankfurt: DB Research.

Foucault T, Kadan O & Kandel E 2005. ‘Limit Order Book as a Market for Liquidity’ *The Review of Financial Studies,* vol. 18, no. 4, pp. 1171-1217

Glosten, LR 1994. ‘Is the Electronic Open Limit Order Book Inevitable?’. *The Journal of Finance,* vol. 49, no. 4, pp. 1127-1161

Goyenko, RY, Holden, CW & Trzcinka, CA 2009. ‘Do Liquidity Measures Measure Liquidity? *Journal of Financial Economics,* vol. 92, no. 2, pp. 153-181

Grossman, SJ & Miller, MH 1988. ‘Liquidity and Market Structure’. *The Journal of Finance,* vol. 43, no. 3, pp. 617–633

Grossman, SJ & Stiglitz, JE 1980. ‘The Impossibility of Informationally Efficient Markets’. *The American Economic Review,* vol. 70, no. 3, pp. 393-408

Handa, P & Schwarts, RA 1996. ‘How Best to Supply Liquidity to a Securities Market’. *The Journal of Portfolio Management,* vol. 22, no. 2, pp. 44-51

Handa, P, Schwarts, RA & Tiwari A 2003. ‘Quote Setting and Price Formation in an Order Driven Market’. *Journal of Financial Markets*, vol. 6, no. 4, pp. 461-489

Hasbrouk, J & Saar, G 2013. ‘Low-Latency Trading’. *The Journal of Financial Markets,* vol. 16, no. 4, pp. 646-679

Hasbrouk, J & Schwartz RA 1988. ‘Liquidity and Execution Costs in Equity Markets’. *The Journal of Portfolio Management*, vol. 14, no. 3, pp. 10-16

Hasbrouck, J & Seppi, DJ 2001. ‘Common factors in prices, order flows, and liquidity’. *Journal of Financial Economics,* vol. 59, no. 3, pp. 383-411

Hendershott, T, Jones, CM & Menkveld, AJ 2011. 'Does Algorithmic Trading Improve Liquidity?'. *The Journal of Finance*, vol. 66, no.1

Hendershott, T & Riordan, R 2012. 'Algorithmic Trading and the Market for Liquidity'. *Journal of Financial and Quantitative Analysis*, viewed 27 February 2013, SSRN: http://ssrn.com/abstract=2001912 or http://dx.doi.org/10.2139/ssrn.2001912

Jain, PK 2003. 'Institutional Design and Liquidity at Stock Exchanges around the World', viewed 8 January 2013, SSRN: http://ssrn.com/abstract=869253 or http://dx.doi.org/10.2139/ssrn.869253.

Jain, PK 2005. 'Financial Market Design and the Equity Premium: Electronic versus Floor Trading'. *The Journal of Finance*, vol. 60, no. 6, pp. 2955-2985

Johannesburg Stock Exchange (JSE) Equity Market Price List v.02, viewed 2013. https://www.jse.co.za/content/JSENoticesandCircularsItems/Equity%20Markets/2013/2013_151B.pdf

Liu, W 2006. 'A Liquidity-Augmented Capital Asset Pricing Model'. *Journal of Financial Economics*, vol. 82, no. 3, pp. 631-671

Menkveld, AJ 2011. 'High Frequency Trading and the New-Market Makers' viewed 4 March 2013, SSRN: http://ssrn.com/abstract=1722924 or http://dx.doi.org/10.2139/ssrn.1722924

Montalvo, JG 2003. 'Liquidity and Market Makers: A Pseudo-Experimental Analysis with Ultrahigh Frequency Data'. *The European Journal of Finance* no.9, pp. 358-378

Muranaga, J 1999. *Dynamics of market liquidity of Japanese stocks: An Analysis of Tick-by-Tick Data of the Tokyo Stock Exchange*, Bank of Japan

O'Hara, M 2004. Liquidity and Financial Market Stability, National Bank of Belgium Working Paper No. 55

Pagano, M & Roell A 1996. 'Transparency and Liquidity: A Comparison of Auction and Dealer Markets with Informed Trading'. *The Journal of Finance*, vol.51, no.2, pp. 579-611

Riordan, R & Storkenmaier, A 2012. 'Latency, liquidity and price discovery'. *Journal of Financial Markets*, vol. 15, no. 4, pp. 416-437

Sarr, A & Lybek, T 2002. *Measuring Liquidity in Financial Markets*, IMF Working Paper WP/02/232

Seppi, DJ 1997. 'Liquidity provision with limit orders and a strategic specialist'. *The Review of Financial Studies*, vol. 10, no. 1, pp. 103-150

Tabb, L 2010, 'Europe's buy-side play catch up with HFT', *Tabb Group*, viewed September 2013, http://tabbforum.com/opinions/europe's-buy-side-play-catch-up-with-hft

Theissen, E 2002. 'Price discovery in floor and screen trading systems'. *Journal of Empirical Finance*, vol. 9, no.4, pp. 455-474

Viswanathan, S & Wang, JDJ 2002. 'Market Architecture: Limit-Order Books versus Dealership Markets'. *Journal of Financial Markets*, vol. 5, no. 2, pp. 127-167

World Federation of Exchanges (WFE) Monthly Reports, viewed 24 September 2013. http://www.world-exchanges.org/statistics/monthly-reports

Wuyts, G 2007. 'Stock Market Liquidity: Determinants and Implications'. *Tijdschrift voor Economie en Management*, vol. 53, no. 2

Zhang, H 2010. *Measuring Liquidity in Emerging Markets*, Department of Finance, NUS Business School, National University of Singapore.

10 APPENDIX

Table A: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2005 - 1 July 2006)

Alpha	ILLIQ	Turnover Ratio	Daily Average Value Traded	Average Market Cap	JSE Liquidity
ABL	28	6	23	30	8
ADH	81	80	82	78	18
ADR	64	38	65	74	22
ADW	86	48	86	90	84
AEG	32	10	31	41	19
AFE	44	43	43	45	75
AFX	46	82	54	37	77
AGL	1	42	1	1	47
ALT	53	67	55	48	70
AMS	18	61	14	6	54
ANG	15	45	12	9	43
APN	25	18	26	28	11
AQP	82	91	78	49	91
ARI	78	75	52	40	80
ARL	50	39	50	56	27
ART	58	53	68	75	41
ASA	10	34	11	11	42
ATN	72	77	67	60	89
AVI	37	20	39	50	37
BAT	55	37	57	61	51
BAW	14	7	16	21	14
BCF	80	84	84	80	88
BEL	88	73	76	76	81
BIL	3	57	3	2	50
BSR	79	36	80	84	40
BVT	17	27	20	18	17
CLH	57	30	58	63	66
CML	63	64	64	62	35
CPI	68	81	69	65	76
DRD	62	51	56	58	65
DSY	43	83	51	29	74
DTC	47	31	49	57	69
ESR	74	60	73	85	28
FBR	65	62	72	77	52
FSR	8	41	9	7	26
GFI	11	5	6	13	23
GND	39	29	40	46	58
HAR	22	8	13	16	29
HCI	83	90	81	54	79
ILA	61	59	63	67	62
ILV	45	23	42	53	53

INL	29	26	32	32	20
INP	23	35	25	24	30
IPL	16	15	17	20	15
ISA	89	86	90	89	83
IVT	75	76	75	70	61
JSE	56	89	53	68	1
LBH	48	70	47	38	68
LEW	40	1	36	51	2
LON	60	74	34	19	56
MDC	41	58	45	42	72
MPC	42	32	44	55	9
MRF	67	65	71	72	64
MSM	24	2	24	34	6
MST	59	25	61	71	46
MTN	6	12	4	8	21
MUR	34	3	30	43	13
NED	19	49	22	14	39
NTC	31	44	35	27	45
OLG	85	71	87	87	86
OMN	54	47	60	64	57
PAM	77	66	70	73	59
PET	90	78	85	82	90
PGR	69	68	66	69	48
PIK	35	50	37	26	38
PNC	70	40	83	83	71
PSG	66	85	74	66	82
PWK	51	87	62	44	73
REM	9	24	10	12	32
RLO	27	21	33	35	33
RMH	30	63	29	17	49
SAB	5	56	8	3	55
SAP	20	4	19	25	34
SBK	4	19	5	5	10
SHF	21	14	21	23	4
SHP	36	55	38	36	44
SLM	12	16	15	15	31
SNT	52	69	46	39	63
SOL	2	9	2	4	24
SOV	76	33	77	81	78
SPG	49	46	48	52	36
SPP	38	28	41	47	25
SUR	73	72	79	79	67
TBS	13	11	18	22	12
TKG	7	17	7	10	16
TMT	84	88	89	86	85
TRU	33	13	27	33	3
VIL	91	54	91	91	5
WBO	71	52	59	59	60

WHL	26	22	28	31	7
WSL	87	79	88	88	87

Table B: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2006 - 1 July 2007)

Alpha	ILLIQ	Turnover Ratio	Daily Average Value Traded	Average Market Cap	JSE Liquidity
ABL	26	2	25	39	3
ADH	79	75	81	77	77
ADR	73	56	73	75	63
ADW	75	24	84	86	33
AEG	34	18	33	37	29
AFE	41	35	41	45	37
AFX	48	69	51	41	70
AGL	1	49	1	1	50
ALT	67	73	58	51	65
AMS	10	63	7	4	61
ANG	14	47	11	9	32
APN	29	13	29	40	14
AQP	71	90	65	36	90
ARI	62	77	45	28	80
ARL	46	37	50	58	38
ART	57	51	69	74	53
ASA	12	43	12	10	42
ATN	72	85	76	61	85
AVI	42	33	46	52	25
BAT	52	30	54	62	27
BAW	13	6	14	21	11
BCF	90	78	85	83	68
BEL	77	70	70	67	82
BIL	3	57	3	2	57
BSR	66	39	68	79	54
BVT	16	25	16	18	21
CLH	54	53	61	64	51
CML	68	74	71	66	74
CPI	80	88	82	68	86
DRD	53	21	56	69	16
DSY	56	83	52	31	81
DTC	47	31	47	55	43
ESR	81	50	77	81	59
FBR	70	60	75	76	64
FSR	8	40	9	8	39
GFI	7	4	5	13	1
GND	37	41	43	46	44
HAR	17	17	15	17	15
HCI	88	89	74	49	89
ILA	65	58	66	72	58

ILV	49	54	49	50	55
INL	33	28	31	27	19
INP	30	45	27	20	47
IPL	19	14	19	22	4
ISA	86	80	88	89	75
IVT	82	82	79	73	83
JSE	45	8	42	59	18
LBH	61	86	63	43	84
LEW	36	3	37	53	2
LON	64	87	38	14	88
MDC	50	72	53	44	76
MPC	39	7	39	54	9
MRF	59	38	57	71	48
MSM	24	1	23	38	12
MST	89	44	72	78	35
MTN	4	20	4	6	23
MUR	35	16	28	32	28
NED	22	55	22	15	46
NTC	23	26	24	26	26
OLG	84	79	87	88	78
OMN	58	48	60	65	49
PAM	63	64	67	70	73
PET	83	84	86	82	87
PGR	74	62	64	63	62
PIK	32	36	35	30	34
PNC	69	52	80	84	45
PSG	60	61	59	60	69
PWK	55	81	62	48	79
REM	11	46	13	12	41
RLO	27	15	30	33	10
RMH	31	65	34	19	56
SAB	6	68	8	3	66
SAP	21	9	21	25	13
SBK	5	29	6	7	22
SHF	20	10	17	24	5
SHP	38	42	36	34	40
SLM	18	34	20	16	36
SNT	43	67	48	42	72
SOL	2	11	2	5	8
SOV	76	27	78	85	31
SPG	44	23	44	56	24
SPP	40	22	40	47	20
SUR	78	71	83	80	71
TBS	15	12	18	23	6
TKG	9	32	10	11	30
TMT	87	91	90	87	91
TRU	28	5	26	35	7
VIL	91	66	91	91	52

WBO	51	59	55	57	67
WHL	25	19	32	29	17
WSL	85	76	89	90	60

Table C: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2007 - 1 July 2008)

Alpha	ILLIQ	Turnover Ratio	Average Spread	Daily Average Value Traded	Average Market Cap	JSE Liquidity
ABL	24	3	17	25	32	13
ADH	90	78	16	80	77	78
ADR	70	53	77	70	76	54
ADW	63	22	8	71	82	30
AEG	26	12	38	24	27	20
AFE	41	43	68	45	49	44
AFX	52	82	41	60	44	81
AGL	1	48	75	1	1	58
ALT	68	76	81	66	52	72
AMS	7	57	90	6	4	64
ANG	12	10	73	7	10	37
APN	35	33	32	35	38	42
AQP	79	91	89	73	25	91
ARI	33	59	80	31	18	75
ARL	48	44	78	51	59	39
ART	67	61	43	76	78	55
ASA	13	41	47	13	12	32
ATN	66	79	74	72	62	82
AVI	45	30	27	47	54	15
BAT	71	46	62	63	69	45
BAW	20	4	60	20	28	3
BCF	87	81	30	87	85	79
BEL	69	64	79	65	63	69
BIL	2	56	61	2	2	63
BSR	56	29	56	58	72	43
BVT	14	25	64	17	17	19
CLH	61	65	76	69	67	65
CML	78	47	22	67	70	49
CPI	81	89	84	84	68	90
DRD	57	23	7	54	71	35
DSY	40	55	28	41	35	53
DTC	46	31	44	48	56	23
ESR	72	54	19	74	79	48
FBR	75	68	46	78	80	62
FSR	9	34	3	9	8	24
GFI	11	11	45	8	14	18
GND	38	36	14	37	42	52

HAR	23	20	49	19	20	38
HCI	77	84	87	61	46	87
ILA	60	35	23	59	73	8
ILV	55	72	52	52	48	76
INL	31	16	37	30	34	9
INP	19	6	31	15	23	4
IPL	25	8	57	26	29	1
ISA	88	63	2	88	90	57
IVT	82	83	72	79	74	85
JSE	49	28	71	46	53	28
LBH	64	74	91	55	45	83
LEW	47	9	67	44	60	5
LON	43	88	86	40	13	89
MDC	51	62	35	50	43	73
MPC	42	13	26	43	57	7
MRF	44	19	1	42	55	41
MSM	29	2	55	27	36	11
MST	83	71	34	85	84	47
MTN	4	17	36	3	6	27
MUR	18	5	50	14	21	14
NED	17	40	58	16	15	33
NTC	32	42	4	33	31	25
OLG	85	86	6	89	88	74
OMN	62	58	85	64	66	59
PAM	74	75	88	68	58	86
PET	76	70	12	77	75	84
PGR	54	45	33	56	65	36
PIK	36	51	29	38	33	50
PNC	73	67	13	82	83	61
PSG	65	85	42	75	61	80
PWK	59	77	20	62	51	70
REM	10	38	65	12	9	40
RLO	37	39	48	36	40	26
RMH	30	60	15	32	19	51
SAB	6	69	63	10	3	71
SAP	21	14	59	23	26	17
SBK	5	26	25	5	7	22
SHF	22	15	11	22	24	12
SHP	34	50	39	34	30	56
SLM	15	37	10	18	16	31
SNT	58	80	83	57	41	77
SOL	3	21	69	4	5	46
SOV	80	49	70	81	86	21
SPG	50	27	18	49	64	10
SPP	39	32	53	39	47	34
SUR	86	73	40	83	81	60
TBS	16	18	66	21	22	16
TKG	8	24	54	11	11	29

TMT	84	90	21	90	87	88
TRU	28	1	24	28	39	6
VIL	91	87	51	91	91	68
WBO	53	66	82	53	50	67
WHL	27	7	9	29	37	2
WSL	89	52	5	86	89	66

Table D: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2008 - 1 July 2009)

Alpha	**ILLIQ**	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ABL	22	9	16	17	23	13
ADH	82	78	18	77	72	78
ADR	66	65	84	72	75	65
ADW	69	41	10	70	82	8
AEG	24	3	31	19	29	4
AFE	50	62	76	52	50	61
AFX	51	69	49	53	47	64
AGL	2	25	67	1	2	23
ALT	61	79	86	61	54	79
AMS	13	51	89	10	6	54
ANG	7	16	75	6	8	28
APN	29	22	39	31	27	36
AQP	75	91	85	79	36	91
ARI	34	43	81	29	19	47
ARL	53	50	83	54	57	59
ART	74	64	36	76	80	56
ASA	8	26	42	11	10	32
ATN	60	72	72	65	63	75
AVI	54	34	41	43	53	30
BAT	71	57	65	64	71	63
BAW	33	2	47	26	40	2
BCF	78	85	37	87	84	85
BEL	62	63	69	66	69	35
BIL	3	46	62	3	1	49
BSR	59	52	58	62	73	44
BVT	16	32	64	21	18	31
CLH	47	60	74	58	62	62
CML	67	68	20	69	70	74
CPI	76	88	78	81	64	89
DRD	49	37	7	55	66	41
DSY	39	53	24	40	34	58
DTC	55	40	40	50	59	37
ESR	72	67	12	75	79	68
FBR	64	83	63	82	74	83

FSR	9	30	3	9	9	26
GFI	11	14	46	8	11	24
GND	40	31	14	41	46	25
HAR	15	8	50	13	16	7
HCI	73	84	88	63	51	87
ILA	65	56	27	68	78	43
ILV	48	71	57	51	45	77
INL	32	10	30	32	38	11
INP	27	15	26	24	25	16
IPL	28	6	54	30	39	12
ISA	89	89	2	90	90	90
IVT	81	77	77	73	68	76
JSE	46	29	66	48	56	38
LBH	68	73	91	47	32	72
LEW	45	24	70	46	55	29
LON	43	58	87	36	15	73
MDC	42	70	33	49	37	70
MPC	38	11	29	38	52	19
MRF	52	20	1	44	60	5
MSM	21	4	59	22	30	14
MST	88	59	21	85	85	45
MTN	1	17	34	2	4	20
MUR	19	1	43	15	24	3
NED	18	39	55	18	14	48
NTC	31	35	6	35	35	33
OLG	86	87	4	88	89	82
OMN	58	49	79	56	65	51
PAM	77	80	90	67	58	80
PET	70	74	15	74	76	69
PGR	85	54	38	60	67	46
PIK	37	45	28	37	28	55
PNC	79	75	19	84	83	66
PSG	84	86	48	78	61	86
PWK	56	81	32	59	49	81
REM	12	23	52	14	13	6
RLO	41	42	56	42	43	42
RMH	30	47	17	34	20	52
SAB	6	61	61	7	3	67
SAP	36	13	45	28	31	10
SBK	5	21	25	5	7	27
SHF	25	18	11	27	26	21
SHP	20	28	35	23	21	34
SLM	17	38	9	20	17	40
SNT	57	82	82	57	42	84
SOL	4	27	73	4	5	22
SOV	80	33	68	83	86	57
SPG	63	48	13	71	77	15
SPP	35	36	51	39	44	39

SUR	90	66	44	80	81	71
TBS	14	12	71	16	22	17
TKG	10	19	53	12	12	1
TMT	87	90	22	89	87	88
TRU	23	7	23	25	33	18
VIL	91	76	60	91	91	60
WBO	44	44	80	45	48	50
WHL	26	5	8	33	41	9
WSL	83	55	5	86	88	53

Table E: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2009 - 1 July 2010)

Alpha	**ILLIQ**	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ABL	27	10	16	17	25	10
ADH	75	73	34	75	70	73
ADR	59	50	74	67	75	54
ADW	87	32	3	85	86	1
AEG	37	1	32	21	39	2
AFE	58	59	81	50	53	58
AFX	74	72	57	55	51	75
AGL	2	30	60	1	2	23
ALT	65	74	75	57	52	72
AMS	15	56	89	9	6	56
ANG	23	22	77	6	8	26
APN	33	19	43	23	22	33
AQP	77	91	79	80	31	90
ARI	39	36	78	29	19	38
ARL	62	47	87	52	61	46
ART	78	64	45	79	81	63
ASA	1	37	44	11	10	36
ATN	76	75	72	73	64	71
AVI	49	39	41	45	54	42
BAT	44	58	56	65	69	62
BAW	17	2	37	32	45	3
BCF	80	81	52	86	83	85
BEL	66	79	66	82	80	74
BIL	4	55	50	3	1	51
BSR	68	38	28	60	73	39
BVT	21	23	62	13	14	22
CLH	86	63	76	58	63	61
CML	57	65	27	64	66	69
CPI	52	90	82	70	55	89
DRD	81	48	9	62	72	32
DSY	14	44	21	35	32	48

DTC	48	33	46	49	58	29
ESR	64	53	11	74	78	47
FBR	61	82	70	76	68	83
FSR	11	35	5	10	9	37
GFI	34	17	42	8	11	19
GND	53	27	15	43	49	18
HAR	26	13	38	14	20	13
HCI	60	87	90	63	48	88
ILA	40	52	40	71	77	45
ILV	46	68	47	48	41	65
INL	42	11	29	31	38	9
INP	31	20	22	30	24	20
IPL	35	5	63	25	33	6
ISA	89	86	4	90	90	84
IVT	79	83	80	78	71	81
JSE	63	29	69	46	57	34
LBH	41	61	71	42	29	57
LEW	43	12	65	44	56	11
LON	32	71	85	40	16	68
MDC	47	76	49	51	40	78
MPC	22	16	36	39	46	24
MRF	70	41	1	53	62	30
MSM	28	7	64	24	30	16
MST	83	49	19	84	85	60
MTN	7	15	23	2	4	8
MUR	45	4	39	28	37	4
NED	18	42	54	15	12	43
NTC	16	43	13	38	34	44
OLG	85	84	6	88	89	87
OMN	69	60	86	59	65	53
PAM	72	77	91	66	59	79
PET	67	57	8	72	76	64
PGR	56	67	51	68	67	67
PIK	29	51	30	36	27	50
PNC	82	70	17	83	82	70
PSG	71	85	53	69	60	82
PWK	51	80	24	56	47	76
REM	8	34	48	18	15	35
RLO	10	31	61	41	44	28
RMH	38	54	18	33	18	55
SAB	3	69	59	7	3	66
SAP	36	26	31	34	35	25
SBK	5	28	26	5	7	27
SHF	13	18	12	22	23	14
SHP	6	9	33	12	17	21
SLM	24	40	10	19	13	40
SNT	73	78	88	54	43	77
SOL	12	21	67	4	5	17

SOV	90	46	68	81	84	52
SPG	55	24	2	61	74	49
SPP	30	25	55	37	42	31
SUR	54	66	58	77	79	80
TBS	9	14	73	16	21	15
TKG	25	8	25	27	28	5
TMT	88	89	20	89	88	86
TRU	19	6	35	20	26	12
VIL	91	88	84	91	91	91
WBO	50	45	83	47	50	41
WHL	20	3	14	26	36	7
WSL	84	62	7	87	87	59

Table F: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2010 - 1 July 2011)

Alpha	ILLIQ	Turnover Ratio	Average Spread	Daily Average Value Traded	Average Market Cap	JSE Liquidity
ABL	20	7	15	18	26	5
ADH	70	66	24	70	71	65
ADR	76	69	77	75	73	67
ADW	91	21	2	89	91	28
AEG	31	5	35	34	40	3
AFE	47	58	80	49	51	58
AFX	63	81	48	63	56	79
AGL	1	29	56	1	2	26
ALT	57	71	73	59	58	66
AMS	8	56	89	8	6	51
ANG	7	23	75	7	8	16
APN	18	19	44	20	20	25
AQP	78	91	74	69	37	90
ARI	27	32	82	25	18	35
ARL	51	52	86	55	62	55
ART	79	62	42	80	81	56
ASA	13	44	50	12	10	43
ATN	71	79	78	74	68	74
AVI	43	41	36	44	50	46
BAT	61	8	34	51	69	63
BAW	37	3	43	29	43	2
BCF	87	89	52	86	82	88
BEL	84	84	65	83	79	84
BIL	2	53	53	2	1	50
BSR	65	59	28	73	75	59
BVT	11	16	67	13	16	11
CLH	56	37	79	57	66	36
CML	54	47	20	54	61	53

CPI	55	83	84	56	44	82
DRD	67	51	9	72	77	60
DSY	36	54	26	40	30	54
DTC	50	46	49	50	57	47
ESR	75	42	7	77	83	48
FBR	64	78	72	67	64	77
FSR	9	34	5	9	9	32
GFI	10	22	47	10	11	12
GND	44	40	14	47	53	30
HAR	23	11	46	15	21	7
HCI	68	85	90	61	48	85
ILA	77	63	51	79	80	57
ILV	53	74	37	53	45	72
INL	34	25	33	37	39	19
INP	22	20	23	26	25	23
IPL	25	4	66	21	28	6
ISA	86	76	4	88	90	75
IVT	72	77	85	71	67	73
JSE	49	30	68	45	59	20
LBH	42	60	62	42	32	61
LEW	45	27	64	43	55	29
LON	40	45	81	32	19	44
MDC	52	82	41	52	36	81
MPC	29	2	40	28	41	4
MRF	58	50	3	60	65	34
MSM	17	6	70	17	27	10
MST	81	55	21	82	85	62
MTN	3	14	29	3	4	21
MUR	35	1	30	33	47	1
NED	16	39	58	14	12	42
NTC	39	35	12	39	33	39
OLG	85	88	8	90	87	87
OMN	69	61	87	62	63	71
PAM	66	80	91	65	60	76
PET	73	73	10	76	74	69
PGR	80	70	61	68	70	70
PIK	28	28	27	35	31	15
PNC	74	75	18	81	78	80
PSG	62	86	71	66	54	86
PWK	48	57	22	48	49	49
REM	19	38	54	24	15	38
RLO	41	33	59	41	46	31
RMH	30	48	19	30	17	40
SAB	6	64	60	6	3	64
SAP	32	13	32	31	34	9
SBK	5	26	25	5	7	22
SHF	21	18	11	22	23	24
SHP	12	9	39	11	14	18

SLM	15	43	13	23	13	41
SNT	59	87	88	58	42	83
SOL	4	24	69	4	5	27
SOV	88	68	63	85	86	78
SPG	60	49	1	64	72	52
SPP	33	17	57	36	38	13
SUR	83	72	55	78	76	68
TBS	14	15	76	16	22	17
TKG	38	31	31	38	35	33
TMT	89	90	17	91	88	89
TRU	24	12	45	19	24	14
VIL	90	67	38	84	84	91
WBO	46	36	83	46	52	37
WHL	26	10	16	27	29	8
WSL	82	65	6	87	89	45

Table G: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2011 - 1 July 2012)

Alpha	ILLIQ	Turnover Ratio	Average Spread	Daily Average Value Traded	Average Market Cap	JSE Liquidity
ABL	20	3	15	18	26	1
ADH	72	76	26	74	70	75
ADR	70	61	61	73	74	64
ADW	91	44	1	88	91	39
AEG	35	14	32	32	41	14
AFE	50	56	80	49	49	50
AFX	76	80	42	65	61	76
AGL	1	17	60	1	3	11
ALT	62	77	66	64	63	72
AMS	14	59	91	12	7	47
ANG	7	7	75	6	9	2
APN	21	31	48	24	18	43
AQP	74	69	57	61	51	49
ARI	31	41	85	29	22	34
ARL	49	36	79	53	64	29
ART	79	60	37	80	83	71
ASA	11	33	54	11	10	27
ATN	77	84	76	79	69	79
AVI	40	13	38	34	43	28
BAT	46	57	22	50	48	61
BAW	28	2	55	27	38	3
BCF	78	74	34	84	81	73
BEL	80	86	83	83	77	85
BIL	3	45	58	3	1	35
BSR	73	71	39	76	76	63

BVT	13	27	70	13	16	24
CLH	59	49	82	63	68	56
CML	51	46	21	51	56	45
CPI	54	72	87	46	36	78
DRD	64	25	8	60	75	25
DSY	29	51	36	38	29	55
DTC	53	64	53	58	55	68
ESR	81	79	7	86	85	74
FBR	66	82	74	70	65	82
FSR	8	32	5	8	8	33
GFI	10	19	51	9	11	9
GND	47	55	16	52	54	48
HAR	24	12	46	16	21	4
HCI	68	88	88	66	47	88
ILA	89	65	49	82	82	69
ILV	60	85	41	62	46	86
INL	37	9	24	33	44	6
INP	26	10	23	26	28	12
IPL	22	4	71	21	27	19
ISA	88	87	4	90	89	83
IVT	75	81	86	71	66	81
JSE	45	11	67	44	60	18
LBH	38	53	63	42	31	51
LEW	44	22	59	43	58	13
LON	36	16	72	28	30	10
MDC	52	78	40	48	32	84
MPC	25	1	52	19	33	8
MRF	69	68	2	72	72	57
MSM	27	47	78	31	24	44
MST	83	58	30	81	84	53
MTN	2	8	31	2	4	7
MUR	41	5	25	40	52	16
NED	19	52	64	22	12	52
NTC	33	38	9	39	35	41
OLG	87	90	12	89	87	89
OMN	56	48	84	55	62	54
PAM	58	63	89	59	59	59
PET	71	73	11	78	78	70
PGR	84	75	44	75	71	77
PIK	34	40	35	41	34	37
PNC	61	50	20	67	73	58
PSG	63	89	65	69	50	90
PWK	55	67	19	54	53	62
REM	17	39	56	23	15	36
RLO	43	43	62	45	45	46
RMH	30	42	17	30	20	65
SAB	5	62	69	5	2	67
SAP	42	18	27	36	42	22

SBK	6	29	29	7	6	26
SHF	18	23	13	20	19	20
SHP	9	15	43	10	13	23
SLM	12	35	14	17	14	40
SNT	57	83	90	56	39	87
SOL	4	24	73	4	5	17
SOV	85	54	47	85	86	60
SPG	65	30	10	57	67	32
SPP	32	28	68	35	37	31
SUR	82	70	50	77	80	80
TBS	15	21	81	14	17	21
TKG	39	20	28	37	40	5
TMT	90	91	33	91	88	91
TRU	23	26	45	25	23	30
VIL	67	37	3	68	79	42
WBO	48	34	77	47	57	38
WHL	16	6	18	15	25	15
WSL	86	66	6	87	90	66

Table H: Liquidity Rankings per Instrument per Liquidity Measurement (2 July 2012 - 1 July 2013)

Alpha	**ILLIQ**	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ABL	39	1	12	18	33	1
ADH	76	68	19	72	70	73
ADR	65	55	55	71	71	59
ADW	88	53	1	89	91	40
AEG	33	11	26	38	49	12
AFE	57	60	76	52	50	74
AFX	73	84	59	70	59	87
AGL	7	25	50	2	3	13
ALT	66	63	71	65	66	61
AMS	26	57	90	23	8	43
ANG	21	10	72	9	12	4
APN	9	32	63	16	15	45
AQP	69	56	13	68	69	56
ARI	24	38	79	28	27	26
ARL	50	27	74	59	67	23
ART	87	78	28	83	84	66
ASA	18	29	56	11	9	31
ATN	86	88	80	79	75	84
AVI	38	18	46	35	39	20
BAT	22	70	35	47	41	78
BAW	36	5	52	27	40	10
BCF	80	83	33	86	82	83

BEL	77	90	88	81	76	90
BIL	6	59	49	3	2	47
BSR	81	51	37	77	78	37
BVT	4	23	73	15	16	27
CLH	49	71	89	67	65	71
CML	47	36	31	44	46	54
CPI	45	49	84	43	34	60
DRD	70	33	9	66	74	33
DSY	37	35	44	26	26	46
DTC	67	52	51	53	54	52
ESR	74	79	7	84	85	72
FBR	58	62	78	57	58	64
FSR	15	31	5	7	7	29
GFI	14	4	47	10	17	2
GND	63	64	16	55	52	70
HAR	28	8	42	25	32	3
HCI	46	74	86	54	47	80
ILA	82	72	45	80	81	53
ILV	52	81	43	60	45	81
INL	44	15	29	37	42	18
INP	40	42	22	30	28	35
IPL	11	2	75	14	24	7
ISA	90	89	4	90	90	86
IVT	71	82	77	69	61	82
JSE	68	24	65	50	62	32
LBH	41	58	70	39	30	58
LEW	51	9	54	46	60	8
LON	55	14	41	31	38	22
MDC	25	50	40	33	23	63
MPC	35	3	60	22	29	6
MRF	64	80	3	78	77	76
MSM	42	54	81	36	25	57
MST	83	73	39	82	83	65
MTN	2	16	38	1	4	21
MUR	53	13	24	42	51	15
NED	12	48	67	21	11	44
NTC	29	30	11	32	31	36
OLG	85	87	14	87	86	89
OMN	8	41	82	49	56	51
PAM	27	61	85	62	64	67
PET	78	45	8	75	79	50
PGR	75	67	30	74	72	68
PIK	54	34	32	40	36	30
PNC	72	47	20	64	68	49
PSG	56	85	69	63	48	85
PWK	60	77	21	61	53	69
REM	10	37	61	19	14	42
RLO	23	40	64	45	43	39

RMH	31	65	18	29	18	55
SAB	3	76	62	4	1	77
SAP	43	17	27	41	44	14
SBK	1	28	34	6	6	28
SHF	30	19	10	24	21	17
SHP	17	12	57	8	10	16
SLM	16	26	15	12	13	34
SNT	62	86	91	58	35	88
SOL	5	22	66	5	5	25
SOV	84	69	48	85	87	62
SPG	61	44	23	56	63	48
SPP	32	20	68	34	37	19
SUR	59	66	58	73	73	75
TBS	20	21	83	20	19	24
TKG	13	43	17	51	57	38
TMT	89	91	36	91	88	91
TRU	34	7	53	17	22	11
VIL	79	46	2	76	80	5
WBO	48	39	87	48	55	41
WHL	19	6	25	13	20	9
WSL	78	75	6	88	89	79

Table I: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2005 - 1 July 2006)

	ILLIQ	**Turnover Ratio**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000				
Turnover Ratio	-0.0834	1.0000			
Daily Average Value Traded	0.9756	-0.0872	1.0000		
Average Market Cap	0.9092	-0.0273	0.9419	1.0000	
JSE Liquidity	0.6065	-0.0652	0.6054	0.4242	1.0000

Table J: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2006 - 1 July 2007)

	ILLIQ	**Turnover Ratio**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000				
Turnover Ratio	0.6338	1.0000			
Daily Average Value Traded	0.9781	0.6082	1.0000		
Average Market Cap	0.8978	0.3504	0.9406	1.0000	
JSE Liquidity	0.6554	0.9730	0.6294	0.3876	1.0000

Table K: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2007 - 1 July 2008)

	ILLIQ	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000					
Turnover Ratio	0.6647	1.0000				
Average Spread	-0.0398	0.2373	1.0000			
Daily Average Value Traded	0.9872	0.6713	-0.0714	1.0000		
Average Market Cap	0.9165	0.4166	-0.2112	0.9338	1.0000	
JSE Liquidity	0.5604	0.9242	0.3050	0.5520	0.2942	1.0000

Table L: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2008 - 1 July 2009)

	ILLIQ	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000					
Turnover Ratio	0.7541	1.0000				
Average Spread	-0.0206	0.1895	1.0000			

Daily Average Value Traded	0.9748	0.7712	-0.0558	1.0000		
Average Market Cap	0.9211	0.5789	-0.1706	0.9444	1.0000	
JSE Liquidity	0.6648	0.9413	0.2701	0.6800	0.4686	1.0000

Table M: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2009 - 1 July 2010)

	ILLIQ	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000					
Turnover Ratio	0.6261	1.0000				
Average Spread	0.0532	0.2812	1.0000			
Daily Average Value Traded	0.9060	0.7029	0.0099	1.0000		
Average Market Cap	0.8698	0.4975	-0.0912	0.9414	1.0000	
JSE Liquidity	0.5972	0.9706	0.2959	0.6885	0.4915	1.0000

Table N: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2010 -1 July 2011)

	ILLIQ	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000					
Turnover Ratio	0.6889	1.0000				
Average Spread	-0.0605	0.1895	1.0000			
Daily Average Value Traded	0.9897	0.7024	-0.1086	1.0000		
Average Market Cap	0.9497	0.5238	-0.1695	0.9579	1.0000	
JSE Liquidity	0.7221	0.9511	0.1813	0.7207	0.5627	1.0000

Table O: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2011 - 1 July 2012)

	ILLIQ	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000					
Turnover Ratio	0.7112	1.0000				
Average Spread	-0.1546	0.0963	1.0000			
Daily Average Value Traded	0.9873	0.7403	-0.1714	1.0000		
Average Market Cap	0.9562	0.5530	-0.2413	0.9592	1.0000	
JSE Liquidity	0.7110	0.9668	0.0770	0.7429	0.5623	1.0000

Table P: Correlation Coefficients of Liquidity Measurement Rankings (2 July 2012 - 1 July 2013)

	ILLIQ	**Turnover Ratio**	**Average Spread**	**Daily Average Value Traded**	**Average Market Cap**	**JSE Liquidity**
ILLIQ	1.0000					
Turnover Ratio	0.5957	1.0000				
Average Spread	-0.2664	0.0262	1.0000			
Daily Average Value Traded	0.9132	0.7232	-0.1984	1.0000		
Average Market Cap	0.8976	0.5593	-0.2633	0.9675	1.0000	
JSE Liquidity	0.5275	0.9540	0.0890	0.6643	0.5026	1.0000