Herding Behaviour and Equity Market Liquidity in the Johannesburg Stock Exchange

Master of Commerce (50% Research) in Finance

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ABSTRACT

This study tests the relationship between equity market liquidity and herding behaviour in the aggregate market portfolio in a South African context and found evidence of herding behvaiour when conditioned on liquidity. The “aggregate market portfolio” refers to the average consensus of all market constituents- in this case the JSE. The analysis is performed through liquidity quartiles on the whole sample period as well as in specific sub-periods with alternative measures of liquidity. The sample period covers January 2000 to December 2021. The results show that a higher level of equity market liquidity is associated with an increase in the tendency for investors to herd towards the market consensus (reduced return dispersions as a result of clustering around the mean market return). However, this research shows that the relationship is dependent on the time period analysed and that the relationship may no longer hold when the relative level of market liquidity (the distribution of daily market liquidity levels) changes.

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1 INTRODUCTION

Traditionally, financial theories attempted to understand financial markets through the context of rational agents. However, this framework has fallen short in explaining the aggregate stock market, the cross-section of average returns, and investor trading behaviour (Barberis & Thaler, 2005). Thus, it seems appropriate to include human emotions in the framework rather than assuming all investors are completely rational all the time. Specifically, academics have begun research into the topic of behvaioural finance which incorporates *irrational* human behaviour into the understanding of how financial markets function.

This study examines the relation between herding behaviour and equity market liquidity in the Johannesburg Stock Exchange (JSE). The term 'herding' can appear in various contexts from zoology and psychology to economics and finance (Spyrou, 2013). Within the financial context, herding behaviour can be defined generally as market participants imitating the actions of other market participants. Various authors have provided their own definition regarding herding behaviour in finance and economics. For example, a collection of investors that trade in the same direction (Nofsinger & Sias, 1999), investors that follow a trend and ignore their initial assessment (Avery & Zemsky, 1998), mutual imitation (Welch, 2000), behaviour that is correlated (Hwang & Salmon, 2004).

As individuals we cannot deny that we influence and are influenced by others in almost every activity that we are involved in. For the same reasons that we may consider trying a new workout routine or purchasing a new product suggested by a friend, that influence includes our investment decisions. That influence we experience extends far beyond the scope of our social network.

There are various reasons posited for herding behaviour which may be rational or irrational. For example, investors may react to new fundamental information and herding behaviour may be rational or investors may irrationally herd due to social trends. Thus, researchers have argued that herding behaviour may lead to increased efficiency while others have argued that herding destabilases prices and may lead to the formation of bubbles in asset prices. For example, Lux (1995) formalised a model which explained the formation of bubbles because of herd behaviour due to mimetic contagion in speculative markets. It is highly likely that both consequences of herding behaviour exist, however, it is difficult to say how the two consequences exist and in what proportion. This is mainly due to two key issues in the study of herding behaviour in financial markets. Firstly, there is a gap between the two main classes of theoretical models of herding. The first class assumes rational investor behaviour while the other assumes non-rational behaviour (Spyrou, 2013). Secondly, as pointed out by Spyrou (2013), it is difficult to fully understand the process of herding behaviour due to the limitations of the main empirical methodologies used to measure the presence of herding.

The reasons for examining the relationship between liquidity and herding behaviour are as follows. Numerous studies have shown liquidity to be an important risk factor in equity returns. For example, in Amihud and Mendelson's (1986) seminal work, the authors found significant evidence for the inclusion of liquidity within asset pricing models. This finding was further corroborated by Amihud (2002), Pástor and Stambaugh (2003), and Liu (2006). Specifically, Liu (2006) posited the use of a Liquidity-Augmented Capital Asset Pricing Model whereby the liquidity factor subsumed the effects of size and value. While the research into the liquidity factor in developing markets is relatively sparse, research has shown positive evidence of the importance of liquidity. For example, Rouwenhorst (1999) reported a correlation between a share's liquidity and return. Bekaert, Harvey and Lundblad (2007) reported the strong ability of the liquidity effect in explaining the variation in share returns. Similar evidence was reported by Muller and Ward (2013) and McKane and Britten (2018). Liquidity has been shown to be highly important in explaining equity returns and is therefore an important aspect driving market participants' decisions.

Tan, Chiang, Mason, and Nelling (2008) showed that herding behaviour can be affected by the state of the market. Similarly, Seetharam (2013) found that in South Africa a market contraction is generally followed by an increase in the level of herding behaviour. However, conversely, Niyitegeka and Tewari (2015) showed evidence of herding behaviour during periods of bull markets. Ababio and Mwamba (2017) examined herding behaviour at an industry and sector level and found evidence of herding only during periods of extremely high or low market returns. Therefore, it appears that the existence of herding behaviour is dependent on the state of the market.

Therefore, examining the relationship between liquidity and herding behaviour can be explained through the following three points. Firstly, liquidity has been shown to be an important aspect of equity returns. Secondly, herding behaviour has been shown to be linked to the state of the market. Lastly, since liquidity is intrinsically linked to the state of the market, the existence of herding behaviour may be linked to the level of market liquidity. For example, it has been argued that liquidity is one of the important fundamentals of financial markets (Ma, Anderson, & Marshall, 2018). This is especially true for emerging markets which are considered to have less liquidity compared to developed markets (Fong, Holden, & Trzcinka, 2017). Through this one can argue that herding behaviour may be dependent on the level of market liquidity. Similarly, one may argue that the level of liquidity may be a result of herding behaviour into a particular share. However, it is unclear whether equity market liquidity induces greater herding behaviour. Devenow and Welch (1996) argued that greater liquidity should encourage greater herding whereas Taylor (2002) argued that due to the relationship between liquidity and asymmetric information (less liquid assets hold greater asymmetric information) one might expect greater levels of herding behaviour in less liquid assets due to the greater amount of asymmetrical information. Therefore, it appears unclear whether herding behvaiour masks liquidity or if liquidity masks herding behaviour.

Therefore, the goal of this study is to determine whether there is a relationship between the level of market liquidity and the existence of herding behaviour. Research into herding behaviour in emerging markets is sparce compared the amount of research published for developed markets. Thus, this study seeks to expand on the limited amount of emerging market research in the area of herding behaviour. Furthermore, this study is the first to study the relationship between herding and equity market liquidity within a South African context. Africa holds a third of the world's mineral resources, 10% of oil reserves and 70% of the global diamond trade. Furthermore, it is estimated that Africa will have the largest workforce by 2040 (Future Agenda, n.d.). Africa is likely to become one of the primary growth markets in the world. Therefore, it is imperative that the amount of research conducted on African financial markets is increased. The JSE is an ideal candidate for research being the largest stock exchange on the African continent and the 16th largest in the world.

The majority of research into herding behaviour and liquidity is independent therefore this research adds to the literature that attempts to bridge the gap between herding behaviour and liquidity. The results and implications of this study will shed light on two topics that are of immense importance for understanding the dynamics of the financial market during periods of extreme uncertainty. By further understanding the effect liquidity has on herding behaviour one can better understand the dynamics that govern financial markets and therefore make better investing decisions. For example, if an investor understands how the level of market liquidity may affect the level of herding behaviour, he/she would be able to better position their trades and investments in a more profitable manner as well as understand the effect such a situation may have on their portfolio's diversification.

The remainder of this study is structured as follows: Section 2 presents a review of the literature; Section 3 sets out the methodology of the study; Section 4 presents the results; Section 5 presents the results of the robustness tests; and Section 6 presents the study's conclusion.

2 LITERATURE REVIEW

2.1 HERDING BEHAVIOUR

One of the earliest and most cited publication on the relationship between social dynamics and stock prices comes from Shiller (1984). The central theme in Shiller (1984) involves the concept of fashion- the roll of mass psychology on financial markets[1]. For example, Shiller (1984) discusses the idea that investing in speculative assets is a social activity. "It is thus plausible that investors' behavior (and hence prices of speculative assets) would be influenced by social movements" (Shiller, 1984, p. 457).

2.1.1 HERDING BEHAVIOUR THEORIES

The cornerstone of many financial theories is rationality and as such one can argue that herding may be a rational decision. For example, a young analyst may be more inclined to follow the consensus, an individual may see others withdrawing funds from the bank and therefore do the same believing the bank may run out of money, other investors may hold knowledge of the profitability of an investment which is only revealed by their actions, or the compensation structures of investment managers may promote following the consensus. In Bikhchandani and Sharma (2000), the authors discuss the difference between true/intentional herding and spurious herding. Intentional herding may not lead to an efficient outcome and may cause excess volatility and market risk. However, spurious herding is an efficient outcome where investors face similar information sets and make similar decisions. For example, if equities become a less attractive investment due to increasing interest rates, then investors will alter their portfolios such that less weight is invested into equities.

Scharfstein and Stein (1990) develop a reputational model for herding. Specifically, managers may, rationally, ignore private information to follow the decisions of other managers[2]. In the model there are two analysts that must make an investment decision between two investments. Neither the two analysts nor the market know which analyst or if both are high quality analysts

[1] Shiller (1984) was published during the time where the consensus of academics and researchers was strictly in line with expected-utility theory and the efficient market hypothesis where the role of market psychology in finance had no standing.

[2] However, Rajan (2006) described this as insurance for underperformance by the manager and thus furthers the argument of the rationality of this type of herd behaviour.

or low-quality analysts. The market's opinion on the quality of the analysts will depend on whether the analysts made the same investment decision or the opposite and update that opinion when the outcome of the investment is observed. There is an equilibrium that exists where the second analyst copies the decision of the first analyst. If the analysts choose the opposite investment decision, then the market will form the opinion that both analysts are of low quality. However, if both analysts make the same investment decision, then the market will view both analysts as high quality. Even if the payoff of the investment is bad, the market will still view the two analysts as high quality and the poor payoff as simply bad luck. Thus, failure when part of the herd is preferable over succeeding apart from it.

However, Zwiebel (1995) describes a situation where it is preferable to always simply succeed when the analyst's quality is measured relative to other analysts which may cause the formation of herding behaviour. In this model, the market compares the performance between managers to form an opinion on the quality and skill of the analysts. Furthermore, analysts are highly risk adverse with regards to being exposed as a poor-quality analyst. Within the model, the highest and the lowest quality of analysts are more likely to choose high risk investments compared to analysts of average quality. This is because a very high-quality analyst will be highly certain of beating the benchmark even with the presence of high-risk investments in their portfolio. Thus, the model explains why the average quality analysts are likely to engage in herd behaviour.

Rational herding behaviour may also be explained by information cascade models. Bikhchandani, Hirshleifer, and Welch (1992) describe an information cascade as a situation where an investor ignores his/her own private information and imitates the actions of investors that came before him/her. Banerjee (1992) described a model where a rational investor, who entered the market at a later stage, should analyse previous investors' decisions since these decisions may possess important information by virtue of entering the market earlier. Trueman (1994) discusses herding behaviour relating to compensation. Specifically, analysts may attempt to match their forecasts with other analysts in order to copy better ability and obtain higher compensation. Graham (1999) developed a model where an analyst is more likely to herd when the analyst has a good reputation or low skills, or if public information is inconsistent with the analyst's private information. This can be seen as rational behaviour in the case of an analyst with good reputation because the impact of being incorrect in going against the consensus is much greater than the impact if the herd's decision was incorrect and the analyst chose to go with the consensus.

Other authors argue that investors may be irrational and may be the cause for herding and financial bubbles. Keynes (1936) argued that social factors may influence investors into copying the actions of others during periods of uncertainty. Shleifer and Summers (1990) present an argument of rational and irrational investors- rational arbitrageurs and irrational noise traders. An irrational shift in investor demand and sentiment will cause some investors to (irrationally) follow the herd. However, the rational arbitrageur will recognise the increased price, which resulted from increased demand, and join the herd with the intention of exiting later to collect profits. Baddeley, Curtis, and Wood (2004) showed that herding behaviour may occur within experts due to information asymmetry and the use of well-known rules (heuristics).

Models have also been presented on how investor sentiment can affect trading behaviour and potentially cause systematic mispricing. Barberis, Shleifer, and Vishny (1998) argue for a sentiment model related to the underreaction and overreaction by investors to information. The authors' results are consistent with the flaws of personal judgment when uncertainty is involved. Hong and Stein (1999) present a model of two types of rational investors. Specifically, slow dissemination of information causes price underreactions in the short run. Momentum traders then exploit this causing a long-term overreaction. Related to this is the argument by Daniel, Hirshleifer, and Subrahmanyam (2005) that suggested biases and overconfidence in private information may lead to excess volatility, autocorrelations, and return predictability.

2.1.2 MEASURING HERDING BEHAVIOUR

Within the literature there are generally two categories of empirical research on herding behaviour. One category involves investigating herding in specific investors, such as, institutional investor herding. The other category investigates herding towards market consensus and uses data on price and market activity.

Lakonishok et al. (1992) proposed a measure of herding behaviour in institutional investors. The logic behind the measure is as follows: if the institutional investors end up on the same side of the market in the buying (or selling) of a particular share then it is concluded that there is herding behaviour. The herding measure is calculated as the number of investors that increased their holding of the share during a time period (net buyers) relative to the total number of investors that traded the share less an adjustment factor. If herding behaviour is present, then there should be evidence of cross-sectional variation in the measure and no variation in the measure from one period to the next if not. The measure is described as:

$$H(i) = \left|\frac{B(i)}{B(i) + S(i)} - p(t)\right| - AF(i) \quad (1)$$

Where B(i) is the number of net buyer institutional investors, S(i) is the number of net seller institutional investors, p(t) is the expected proportion of institutional investors buying in that period relative to the number of active investors, and AF(i) is the expected value of $\left|\frac{B}{B+S} - p\right|$ under the null hypothesis of no herding behaviour.

Christie and Huang (1995) argued that during periods of increased market volatility there will likely be herding behaviour. Specifically, during periods of increased volatility and uncertainty investors are more likely to ignore their personal beliefs and conform to the market consensus. Therefore, the investors' returns should show relatively low dispersion and cluster around the return of the market. This measure is defined as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N - 1}} \quad (1)$$

Where $R_{i,t}$ is the observed return of share i at time t, $R_{m,t}$ is the market return at time t, and N is the number of shares. As equation 2 shows, the CSSD is simply the standard deviation of the shares' returns with the market return acting as a proxy for the mean return. In order to detect the existence of herding behaviour the value calculated form Equation 2 is used as the independent variable in the following regression:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \quad (2)$$

Where D_t^L and D_t^U are dummy variable which hold a value of 1 if the return lies in the lower or upper tail of the return distribution and α is the average dispersion of the sample excluding the area covered by the dummy variables. During periods of increased uncertainty, rational asset pricing predicts that due to the different market return sensitivities of shares periods of market stress should cause increased levels of dispersion. Therefore, negative values for $\beta_1$and β_2 indicate the presence of herding behaviour (Christie & Huang, 1995).

However, the CSSD measure is sensitive to outliers and thus Christie and Huang (1995) proposed the use of the Cross-Sectional Absolute Deviation (CSAD):

$$CSAD_t = \frac{\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|}{N} \tag{3}$$

By taking the absolute difference instead of the squared difference in returns, outliers receive less weight in the calculation. Specifically, the weights of the absolute difference in returns receive equal weighting in the CSAD equation. To determine the presence of herding behaviour the regression of Equation 3 is used again[3].

As discussed above, there is an increasing and linear relationship between share return dispersion and the market return. However, Chang, Cheng and Khorana (2000) argued that this relationship may be non-linear. The authors expanded on the work of Christie and Huang (1995) and presented the following regressions to test for herding behaviour:

$$CSAD_t^{UP} = \alpha + \beta^{UP}\left|R_{m,t}^{UP}\right| + \gamma^{UP}R_{m,t}^2 + \epsilon_t \tag{4}$$

$$CSAD_t^{DOWN} = \alpha + \beta^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma^{DOWN}R_{m,t}^2 + \epsilon_t \tag{5}$$

Where $\left|R_{m,t}^{UP}\right|$ ($\left|R_{m,t}^{DOWN}\right|$) is the absolute market return on day t when the market is up (down). If β is statistically positive, then the assumptions of rational asset pricing models hold and the relationship between dispersion and the market return is linear. Looking at the nonlinear term, if γ is statistically negative, then during periods of large prices changes dispersion will decrease disproportionately to what rational asset pricing models expect and indicates the presence of herding behaviour. However, if γ is positive then it implies that traders are trading according to their own investing beliefs (increased individuality).

2.1.3 INSTITUTIONAL INVESTOR HERDING BEHAVIOUR

Lakonishok et al. (1992) investigated institutional investor herding behaviour and found that pension fund managers do not engage in herding behaviour, although there was evidence for herding behaviour in smaller stocks. By employing the measure of herding behaviour developed by Lakonishok et al. (1992), Grinblatt et al. (1995) examined the mutual fund

[3] CSAD is not a measure of herding behaviour. It is used in the relationship between $CSAD_t$ and $R_{m,t}$ to test for the presence of herding behaviour.

industry and found no evidence of significant herding behaviour. Similarly, Wermers (1999) found evidence consistent with the previous studies although the author did find evidence of herding within smaller market capitalization shares as well as herding in funds with a growth orientation. The implication of these papers suggests only weak evidence of herding behaviour by institutional investors. A key issue of the research discussed above is that it is difficult to separate momentum from true herding behaviour. For example, Nofsinger and Sias (1999) found that there exists a positive relationship between the change institutional investor ownership and the market return. Thus, as Nofsinger and Sias (1999) suggest, this relationship may be the result of momentum trading or because institutional investors can have a greater impact on the price of a share relative to individual retail investors.

An interesting argument made by Sias (2004) suggests that herding behaviour in the institutional investor space may be the result of inferring information from each other's trades. Li and Yung (2004) found that after controlling for momentum trading, there was a positive relationship between the change in institutional investor ownership and the returns in the American Depositary Receipt market. Research by Gutierrez and Kelley (2008) suggests that the purchases by institutional investors may have a longer lasting effect on security prices compared to institutional sales. The authors suggest that the latter may be due to liquidity reasons whereas the former may be due to informational reasons. By using a measure of herding behaviour based on Lakonishok et al. (1992), the authors found no evidence of herding behaviour expect in smaller shares however, there was no evidence of a destabilising effect on prices. Choi and Sias (2009) found a correlation between the proportion of institutional investors purchasing instruments in an industry during quarter t and the proportion of institutional investors that purchased in the previous quarter t-1. Furthermore, the authors remark that the evidence of institutional investor herding behaviour is larger in more volatile and smaller industries and that such behaviour can cause a mismatch between market prices and the industry's fundamental value.

Wylie (2005) conducted research on equity fund managers in the United Kingdom (UK) and found evidence of some herding behaviour although the herding was exclusive to shares that appear on the extreme ends of the distribution of market capitalisations. Further, Kim and Nofsinger (2005) performed a comparative study between the US and Japan and found lower levels of institutional herding in Japan compared to the US. However, the price impacts were much greater in Japan. Furthermore, the authors suggest that the level of institutional herding and the effects are dependent on the overall economic health and the level of regulation.

Consistent with these results, Iihara et al. (2001) found evidence of herding behaviour by both institutional investors and foreign investors and that the herding behaviour impacts the prices of shares. Similarly, Chang and Dong (2006) used data from 1975 to 2003 and found that for institutional investors in Japan there was a positive relationship between institutional herding and unsystematic risk. In a study of German mutual funds, Walter and Weber (2006) found that a large portion of the herding was due to spurious herding due to changes in the composition of the benchmark index. However, Walter and Weber (2006) found no evidence that herding behaviour of institutional investors neither greatly stabilises nor destabilises share prices.

In a study on the Polish market, Voronkova and Bohl (2005) found that pension fund managers are more likely to display herding behaviour and make use of positive-feedback trading strategies (momentum trading) compared to pension fund managers in more developed markets. The authors attribute this to the greater levels of market concentration and regulation. Furthermore, the authors found that the trading decisions by the pension fund managers did not significantly influence share prices. Chang (2010) studied herding behaviour of foreign institutional investors in emerging markets. The author found that when foreign institutional investors increased their holding of shares in a particular sector, mutual fund managers and margin traders did the same- this result was robust to controlling for momentum trading effects. The implication of Chang's (2010) results is the potential for institutional investors to destabilise prices. In contrast to this, Bowe and Domuta (2004) found that herding behaviour in the Jakarta Stock Exchange was not price destabilising, and that momentum trading did not significantly influence Indonesian stock markets during the Asian crisis of 1997. Choea, Khoa, Stulz (1999) employed data from 1996 to 1997 and found evidence of both herding behaviour and momentum trading by foreign investors before the crisis. Similar evidence of herding behaviour was found by Holmes, Kallinterakis, and Ferreira (2013). The authors examined institutional investing in Portugal and found that the herding behaviour of institutional investors tended to be intentional and likely because of reputational reasons.

Turning to the evidence of herding behaviour by hedge fund managers, Brunnermeier and Nagel (2004) found that many of these sophisticated investors exploited the rise in technology stocks during the 1998 to 2001 period and subsequently reduced exposure before the massive fall in prices. Fung and Hsieh (2000) found that trading by hedge funds accounts for a significant amount of the trading volume and can influence the prices of securities during some periods of increased volatility. Despite the evidence from Brunnermeier and Nagel (2004) that the institutional investors took advantage of irrational investor sentiment towards technology stocks, Fung and Hsieh (2000) found that the institutional investors (the hedge funds) do not intentionally induce investors to herd in certain positions. In line with the results of Graham (1999), Boyson (2010) found evidence of greater herding behaviour by the more senior and experience hedge fund managers. Consistent with the evidence above, Boyd, Buyuksahin, Harris, and Haigh (2010) found herding behaviour by hedge funds in US futures. The authors argue that herding behaviour by sophisticated institutional investors may serve to stabilise prices in the futures market.

Research into the herding behaviour of individual investors versus institutional investors has shown similar results. Kim and Wei (1999) found that individual investors display significantly more herding behaviour than institutional investors in Korea. Further, the foreign investors displayed more herding behaviour than local investors. In studies of Chinese markets, Tan, Chiang, Mason, and Nelling (2008) found evidence of herding behaviour in A-share and B-share[4] markets. Li, Rhee, and Wang (2009) posit that herding behaviour by institutional investors is more severe than individual investors. The argument is that individual investors tend to diversify their holdings over a wider range of shares whereas institutional investors take more selective positions. Furthermore, the authors indicate that individual investors are highly influenced by publicly available information and events that generate a lot of attention.

There appears to be some consistency in the research on institutional investor herding behaviour. Specifically, there appears to be a relationship between how developed a market is and the level of regulation and the level of herding behaviour identified. However, the literature is unclear on whether institutional herding creates greater levels of efficiency and price stabilisation or not. This is a key question as it would provide guidance as to whether the herding behaviour observed is spurious or intentional.

2.1.4 AGGREGATE MARKET HERDING BEHAVIOUR

As previously discussed, there are generally two areas of research into herding behaviour. Empirical research on herding behaviour using aggregate market behaviour generally uses the methodology of Christie and Huang (1995) and Chang et al. (2000) to test for herding towards the market average. During periods of increased market stress, Christie and Huang (1995) predict that herding behaviour should induce a decrease in the dispersion of returns. However, the evidence of their study showed significant increases in the dispersion of returns during

[4] A-share markets are typically dominated by individual domestic investors and B-share markets are dominated by foreign institutional investors (Chiang, Mason, & Nelling, 2008).

periods of large price changes. This finding is consistent with rational asset pricing and thus inconsistent with the presence of herding. Based on this finding, Christie and Huang (1995) conclude that herding behaviour is not an important factor in models of asset returns. Chang et al. (2000) reported no evidence of herding behaviour in the US and Hong Kong markets and only partial evidence for Japan. However, significant evidence of herding behaviour was reported for the two emerging markets in their study: South Korea and Taiwan. Furthermore, for the markets that displayed herding behaviour, macroeconomic information had a much greater impact on the behaviour of investors than firm-specific information.

Hwang and Salmon (2004) adopt a methodology similar to Christie and Huang (1995) but instead of focusing on the variability of returns, Hwang and Salmon (2004) focus on the variability of factor sensitivities. The methodology separates herding behaviour due to market sentiment and adjustments to fundamental news. The results show significant herding behaviour in US and South Korean markets. Further, the herding behaviour is not dependent on macroeconomic factors or current market conditions. Hwang and Salmon (2004) also demonstrate that herding behaviour decreased during the Asian and Russian crises. Similarly, in a study of nine American Exchange Traded Funds (ETFs) conducted by Gleason et al. (2004), the authors do not find evidence of herding behaviour during extreme market movement periods.

Caparrelli et al. (2004) employed the non-linear approach of Chang et al. (2000) and the methodology of Hwang and Salmon (2001) to investigate the presence of herding in the Italian Stock Exchange and found evidence consistent with Christie and Huang (1995). In contrast, Henker et al. (2006) employed daily and intraday data on the Australian market and found evidence consistent with rational asset pricing models. However, Henker et al. (2006) emphasised that herding behaviour was not tested on specific subperiods thus, the presence of herding during bubbles, for example, cannot be ruled out. In a study using data from the Athens Stock Exchange, Caporale et al. (2008) used the methodology of Christie and Huang (1995) and Chang et al. (2000) to test for herding behaviour of daily, weekly, and monthly intervals. While the authors found evidence of herding in each of the three intervals, the daily interval displayed the strongest level of herding behaviour. Furthermore, the authors indicated that investors have displayed more rationality since 2002. Economou et al. (2011) tested for herding behaviour in Portuguese, Spanish, Italian, and Greek markets using the non-linear methodology of Chang et al. (2000). The results did not indicate herding behaviour in the Spanish market although herding was detected for the Italian and Greek markets. A unique result of their research was evidence of significant co-movement of return dispersion across the markets. Such a finding has important implications on the potential diversification benefits for investors investing across these markets.

The research on herding behaviour of the aggregate market suggests that the period in which herding behaviour is being tested is an important consideration. Furthermore, the presence of herding in one market does not necessarily imply the existence of herding in another. However, one cannot rule out the effect herding in one market may have on another due to globalisation and the extent of interconnectedness equity markets experience. One key aspect that the literature has not addressed is the length of period that herding may exist for. Understanding how the herding behaviour in one market can affect another as well as the duration of this effect is of great importance for investors' diversification needs.

2.1.5 ANALYST RECOMMENDATION HERDING BEHAVIOUR

Various authors such as Scharfstein and Stein (1990), Trueman (1990), and Graham (1999) have argued that analysts herd due to reputational or compensational reasons or due to imitating the actions of better analysts which leads the analyst to underweight his/her private information and thus herd towards the market consensus. For example, Hirshleifer et al. (1994) developed a model which demonstrated herding when private information was made available to some before others.

The empirical research of analysts' recommendations seems to match the theories of the above authors. Cote and Sanders (1997) examined herding behaviour in an earnings forecast context and found increased levels of herding behaviour for analysts that are concerned with their reputation and their consensus forecast credibility. An interesting result of their study was that an analyst's forecast ability displayed an inverse relationship to the level of herding behaviour. Graham (1999) confirmed the existence of herding behaviour with regards to newsletter analyst strategies. Similarly, Hong, Kubik, and Solomon (2000) explored the link between herding and reputation. The authors found that inexperienced analysts are more likely to face termination compared to more experienced analysts for inaccurate forecasts. One can argue that this creates an incentive for analysts to herd. Further, inexperienced analysts are more likely to face termination for bold forecasts and tend to update their forecasts more frequently. These results imply that inexperienced analysts are more likely to herd towards the market consensus (Hong et al., 2000).

Chevalier and Ellison (1999) examined mutual fund managers and found evidence that "termination" is more sensitive to the performance of younger inexperienced managers. Furthermore, the relationship between performance and termination implies that the younger managers avoid idiosyncratic risk and are incentivised, due to career concerns, to herd into popular sectors. Security analysts' recommendations were shown to have a significant influence on the next two analysts' recommendations (Welch, 2000).

It has been shown that there exists a positive relationship between the level of herding behaviour by analysts and the level of difficulty of the analysis. For example, analysts that focus more on diversified companies (geographically and/or industrially) display higher levels of herding (Kim & Pantzalis, 2003). Kim and Pantzalis (2003) also noticed that the market value of companies that the analysts herd towards have a reduced market value which implies that the market punishes the herding behaviour of analysts. Olsen (1996) argued that our natural desire for consensus is what causes the herding behaviour of analysts' forecasts. Further, this herding behaviour creates a positive bias and greater inaccuracy of the forecasts (Olsen, 1996). In addition, Olsen (1996) argues that investors incorrectly infer reduced risk from the reduced dispersion[5] as well as form a positive bias to large future returns.

The research into analyst herding behaviour paints an interesting picture regarding the concept of The Other. There appears to be a consensus that herding behaviour is mainly a result of reputational reasons. An analyst, particularly a junior, may face the punishment of being regarded as The Other if their recommendations or forecasts do not align with the consensus of other analysts. However, it appears that this concept may diminish as one moves higher up the ladder of experience. Specifically, an experienced analyst may have more freedom in expressing their non-consensus views. Furthermore, an experienced analyst may be rewarded for such views.

2.1.6 SOUTH AFRICAN RESEARCH

Gilmour and Smit (2002) investigated institutional herding behaviour in the South African unit trust industry. The two main findings of the paper can be summarised as follows. Firstly, when unit trust funds were separated by risk profile the results indicated a relationship between the risk profile and the level of institutional herding. Specifically, the riskier and more aggressive funds displayed higher levels of herding. The author attributes this to the funds possessing less accurate information. The second finding of the paper was the positive relationship between

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[5] The reduced dispersion of forecasts occurs due to the herding of analysts towards the market consensus which also increases the mean of the distribution of the earnings forecasts (Olsen, 1996).

the level of herding behaviour and the level of uncertainty in the market. What is interesting about this finding is the evidence of a volatility ceiling whereby volatility in excess of this ceiling did not induce greater levels of herding behaviour.

Seetharam (2013) investigate aggregate market herding behaviour conditional on the market cycle. Over the entire sample period there is no evidence of the presence of herding behaviour. However, when conditioned on the market cycle, the author found evidence of herding behaviour during down markets. Furthermore, the level of herding appeared to increase right before a significant market contraction.

Sarpong and Sibanda (2014) conducted research on institutional herding behaviour in mutual fund managers. The authors found that funds that act contrarian to the market tend to outperform mutual funds that conform with the herd. The authors' overall conclusion is that these contrarian funds may help to stabilise share prices during periods of market uncertainty.

Shrotryia and Kalra (2020) examine herding behaviour towards market consensus during low and high volatility market conditions in the BRICS' markets. The authors found weak evidence of herding behaviour (towards the market consensus) for the TOP 40 JSE constituents over the full sample period for monthly price data. Furthermore, it was shown that herding behaviour was independent of the current state of the market (low and high volatility)- a finding that contrasts Seetharam (2013).

Munetsi and Brijlal (2021) investigated herding behvaiour on the JSE for the period of January 2007 to December 2017. This paper deviated from other research of South African herding behaviour in that the authors used data for the JSE tradable sector indices. The results displayed no evidence of herding behaviour during the pre-crisis period for all three indices. During the crisis period, however, the results indicated the presence of herding for all three indices. Interestingly, during the post-crisis period, only one out of the three indices evaluated indicated the presence of herd behaviour. Overall, the results of the paper indicated that herding behaviour becomes much more prevalent during periods of increased market volatility.

The majority of herding behaviour research in South Africa focuses on aggregate market herding. There appears to be a consensus that herding behaviour is only detected during periods of increased volatility or uncertainty. The exception would be Shrotryia and Kalra (2020), however, one could argue that the use of monthly data was unable to capture herding behaviour.

2.2 LIQUIDITY

This section outlines some of the seminal research into liquidity's relationship with asset returns. While this research is not explicitly concerned with the relationship between liquidity and equity returns, it is important to understand the prevailing papers to enable a deeper understanding of the mechanics between liquidity and equity returns in order to understand why liquidity may have an effect on herding behaviour.

2.2.1 GLOBAL LIQUIDITY RESEARCH

Liquidity has been proposed as a potential pervasive factor in the explanation of share returns. In their seminal work Amihud and Mendelson (1986) used the bid-ask spread to proxy for illiquidity and showed a positive relationship between share returns and illiquidity. Furthermore, Datar, Naik, and Radcliffe (1996) come to a similar conclusion using share turnover as the proxy for liquidity. In contrast, Fama and French (1992) argue that while it is important for academics and researchers to study the role of liquidity in the market, it is unnecessary to include liquidity in asset pricing models since liquidity's effects are subsumed by size and value factors (book-to-market ratios). Jacoby, Fowler and Gottesman (2000), Pastor and Stambough (2003), Amihud (2002), and Liu (2006) all found liquidity to be an important component in the explanation of share returns. Acharya and Pedersen (2005) developed a model which includes a liquidity factor into the standard CAPM and showed an improvement in the model's explanatory power and predictiveness. More recently, Ibbotson, Chen, Kim and Hu (2013) showed that a liquidity investment style is able to perform well and is sperate from other well-known investment styles such as size, value, and momentum. An interesting paper by Hartian and Sitorus (2015) found evidence of a positive relationship between liquidity and equity returns for developing markets and the opposite relationship for developed markets.

Liquidity therefore appears to be an aspect of risk in equity returns that the market considers when performing trades. For example, liquidity risk was shown to be an important consideration for investors and fund managers when holding relatively illiquid shares during market downturns. Lustig and Chien (2005) showed that investors price liquidity risk through a greater required return on shares based on their relative illiquidity. Specifically, a larger required return was due to the costs involved when holding illiquid shares during a market downturn that cannot be easily sold. According to Liu (2006), a liquidity factor can capture distress risk more accurately than the traditional size and value factors of the Fama and French Three-Factor Model. Liu (2006) employed the use of a factor that captured multiple dimensions of liquidity. Liu (2006) developed a model which included the multi-dimensional liquidity factor in the standard CAPM. The results showed that the model appeared to be stronger than the Three-Factor Model.

Studies have therefore shown that the inclusion of liquidity into the study of financial markets can take on many forms. Furthermore, this inclusion appears to be important no matter the form. One can argue that this is due to the multifaceted nature of liquidity and its inherent importance for financial markets as a whole: from the liquidity of an individual share to the overall level of market liquidity. It is important to note that the relationship may not operate identically for developed and developing markets. One could argue that this may be a result of the level of integration an equity market has to the economy as well as its level of correlation or dependence on other economies.

2.2.2 SOUTH AFRICAN RESEARCH

Research into the effect of liquidity on equity returns within a South African context is sparce. To my knowledge the earliest of such research was conducted by Bradfield, Barr, and Affleck-Graves (1988). The paper was an empirical testing of the validity of the CAPM on the JSE whereby liquidity was tested as an additional effect. Consistent with Roll (1984) the authors employed an implicit bid-ask spread, which was calculated directly from the share prices, as a proxy for the liquidity effect. The authors' results indicated no significant liquidity effect on the JSE. However, Rouwenhorst (1999) employed share turnover as a proxy for the liquidity effect and found slightly more favourable evidence for the liquidity effect with regards to the correlation between liquidity and share returns. Interestingly, the other factors tested in the paper (momentum, size, beta, and value) showed evidence of a strong correlation with turnover. This indicates that there may exist an interaction between liquidity and other well-established factors. Bekaert, Harvey, and Lundbald (2007) used the number of zero daily returns as the proxy for liquidity. The authors found strong evidence in favour of the importance of the liquidity effect in share returns. Specifically, the authors found that the measure of liquidity employed significantly predicted future returns. The implication of this is that liquidity appears to be a priced factor. Furthermore, unexpected liquidity shocks were related to shocks in share prices.

Therefore, research on the importance of liquidity in equity markets in a South African context are consistent with the seminal research conducted on developed equity markets. Specifically, liquidity is evidently important in explaining equity returns as well as that there appears to be a link between liquidity and other risk factors. One can argue that this is due to the nature of liquidity: its effect can be seen at the lowest level (individual share level) and the highest level (the market itself).

2.2.3 MEASURING LIQUIDITY

There are multiple dimensions concerning equity market liquidity. These dimensions can include the trading quantity, trading cost, trading speed, and the price impact (Liu, 2006). Specifically, trading quantity refers to the number of shares of a particular company traded during a specific period. Trading cost refers to the extra costs incurred when attempting to buy or sell a share. Trading speed refers to how quickly a share can be bought or sold. Lastly, price impact refers to the change in price when buying or selling shares in a particular company. Furthermore, measures of liquidity can be divided into direct and indirect measures. The former involves transaction data, for example, trading volume. whereas the latter refers to the characteristics of the asset, for example, the bid-ask spread (Houweling, Mentink, & Vorst, 2005).

Due to the multi-dimensional nature of liquidity, it is unlikely that a single measure will be able to capture all aspects of liquidity. Thus, there are many measures that authors have used in their research on liquidity. Amihud and Mendelson (1986) used the bid-ask spread to analyse the cross-section of share returns. Brennan and Subrahmanyam's (1996) measure assessed the price impact of a single unit trade size. Amihud's (2002) liquidity measure (hereafter referred to as Amihud's measure of liquidity) used the average price impact relative to trading volume. Amihud (2002) found a positive relationship between illiquidity and share returns on the NYSE. Pástor and Stambaugh (2003) found evidence that returns vary with their sensitivity to market-wide liquidity. Liu (2006) measured liquidity as the standardised turnover-adjusted number of zero daily trading volumes. Idzorek, Xiong, and Ibbotson (2012) looked at US mutual funds and found evidence that turnover demonstrated the best explanatory ability. Similarly, Haugen and Baker (1996) and Datar, Naik, and Radcliffe (1998) when liquidity is measured through turnover, illiquid shares tended to outperform liquid shares.

The concept of liquidity is clearly difficult to define. This is due to the multifaceted nature of liquidity. It should be of no surprise that there exist multiple measures that attempt to measure liquidity. Therefore, studies that investigate liquidity should always be considered in the context of the measure of liquidity employed.

3 DATA AND METHODOLOGY

This study seeks to examine the relationship between equity market liquidity and herding behaviour towards the market consensus in the JSE. Specifically, whether the presence of herding behaviour is conditional on liquidity. This study can be viewed as an extension to Galariotis, Krokida, and Spyrou (2016) which found significant evidence of the presence of herding behaviour for highly liquid stocks in G5 markets when conditioned on the liquidity of stocks. However, this research expands on the number of sub-periods investigated, uses alternative proxies for market liquidity and market return as well as tests the robustness of the results in relation to the relative level of market liquidity.

3.1 DATA

For the empirical analysis, daily data is employed from shares listed on the JSE for the period of January 2000 to December 2021 as obtained from Bloomberg and the sample of shares is restricted to those that have continuously traded since January 2000 (46 shares).

The sample period is divided into three sub-periods to determine the stability of the results during the financial crisis of 2008-2009. The method of dividing the sample period follows Forbes and Rigobon (2002) and Baur (2012) whereby the events are announced by official sources. In line with Galariotis et al., (2016), this research adopts the Federal Reserve Board of St. Louis and the Bank of International Settlements (BIS,2009) timelines. The three periods are therefore defined as: Jan 2000 to July 2007, August 2007 to March 2009, and April 2009 to December 2019 for per-crisis, crisis, and post-crisis, respectively. Furthermore, a "Covid-19" sub-period is included with the start date of the sub-period set as January 2020 until the end of the sample (December 2021).

3.2 DESCRIPTION AND METHODOLOGY

The CSAD was initially proposed by Christie and Huang (1995) in their seminal work as a robustness test to the CSSD. During periods of increased uncertainty, investors are more likely to conform to the market consensus and thus, the investors' returns will display reduced dispersion due to the clustering of returns around the market mean return. Furthermore, since the CSSD measure of herding behvaiour is more sensitive to outliers, this research makes use of the CSAD:

$$CSAD_t = \frac{\sum_{i=1}^{N} \left| R_{i,t} - R_{m,t} \right|}{N} \quad (7)$$

Where $R_{i,t}$ is the observed return of share i at time t (price return), $R_{m,t}$ is the market return at time t, and N is the number of shares. Consistent with the work of Chang et al. (2000), this research uses the CSAD to proxy for the Expected Cross Sectional Absolute Deviation (ECSAD) of returns and the market return to proxy for the Expected Market Return. The following regression is used to detect herding behaviour:

$$CSAD_t = \alpha + \beta\left|R_{m,t}\right| + \gamma R_{m,t}^2 + \varepsilon_t \tag{8}$$

Where $\left|R_{m,t}\right|$ is the absolute return on the market and $R_{m,t}^2$ is the market return squared. The coefficient β will be statistically significant and positive if the rational asset pricing assumptions hold which also implies a linear relationship between CSAD and the market return. Rational asset pricing predicts a positive linear relationship between the market return and dispersions because of the differing sensitivities individual shares have to the market. The coefficient γ is the non-linear term of Chang et al. (2000), if γ is statistically negative this implies the presence of herding behaviour. During periods of increased uncertainty, the CSAD should decrease in a non-linear fashion; disproportionate to what rational asset pricing expects. Alternatively, if γ is statistically significant and positive, this implies that investors are increasing their individuality with regards to their trades.

This research uses the illiquidity measure of Amihud (2002) which measures the price sensitivity to trading volume. Sarr and Lybek (2002) argue that liquidity measures that incorporate volume in measuring whether orders that are large and numerous have a marginal impact on asset prices. Using the methodology of Karolyi, Lee, and Van Dijk (2012), the liquidity measure is modified into a liquidity measure instead of an illiquidity measure:

$$Liq_{i,t} = -\log\left(1 + \left(\frac{\left|R_{i,t}\right|}{P_{i,t}VO_{i,t}}\right)\right) \tag{9}$$

Where $R_{i,t}$ is the return of share i at time t, $P_{i,t}$ is the price of share i at time t, and $VO_{i,t}$ is the trading volume of share i at time t. The mean liquidity is averaged across all shares in the sample in order to arrive at a measure that proxies for market liquidity:

$$Liq_{m,t} = \frac{1}{N}\sum_{i=1}^{N} Liq_{i,t} \tag{10}$$

To test the relationship between herding behaviour and equity liquidity, Equation 8 is modified into the following form:

$$CSAD = \alpha + \beta_0 \left| R_{m,t} \right| + \beta_1 R_{m,t}^2 + D_1 \beta_2 R_{m,t}^2 + D_2 \beta_3 R_{m,t}^2 + \varepsilon_t \quad (11)$$

Where D_1 is a dummy variable which takes a value of 1 if liquidity is in the upper quarter of the distribution and 0 if not. D_2 is a dummy variable which takes a value of 1 if liquidity is in the lower quarter of the distribution and 0 if not. This methodology allows capturing herding behaviour during periods of high and low market liquidity (Galariotis et al., 2016).

As previously discussed, equity liquidity contains multiple dimensions, and it is unlikely that there is a single best measure of liquidity which is able to capture all aspects. Thus, to confirm the robustness of the results this research will employ other measures of liquidity namely, the effective percentage bid-ask spread, as defined in Equation 12, which measures the cost dimension of equity market liquidity for each share i at time t (Cobandag Guloglu and Ekinci, 2022). And turnover, defined in Equation 13, which measures the trading quantity dimension of equity market liquidity for each share i at time t. For each measure of liquidity, the overall market liquidity for period t is measured as the mean over the shares.

$$\%\, effective\ spread_i = 2 * |P_i - Midpoint_i| / Midpoint_i \quad (12)$$

Where P_i is the closing price of share i on day t and $Midpoint_i$ is the midpoint of the bid and ask prices of share i on day t.

$$Turnover_i = Volume_i / Outstanding_i \quad (13)$$

Where $Volume_i$ is the number of shares trade for share i on day t and $Outstanding_i$ is the number of shares outstanding for share i on day t.

3.3 DESCRIPTION OF OVERALL RESEARCH DESIGN

Unit root tests and serial correlation are reported on the market return and CSAD variables to test if the data displays autocorrelation or non-stationarity. The methodology of Newey and West (1987) is implemented for the regressions to account of heteroscedasticity and autocorrelation.

Following this, the regression of Equation 8 will be performed on the full sample period and each of the four sub-periods. This leads to the first set of null hypotheses:

H_0: the linear term β is positive which implies the absence of herding behaviour.

H_0: the non-linear term γ is positive which implies the absence of herding behaviour (i.e., there is increased individuality with regards to investors' trades).

The regression in the form of Equation 11 is then performed to analyse the relationship between liquidity and herding behaviour in the full sample period and in each of the sub-periods. This is aimed at specifically testing the following null hypotheses:

H_0: the linear term β_2 is positive which implies the absence of herding behaviour for high liquidity shares.

H_0: the linear term β_3 is positive which implies the absence of herding behaviour for low liquidity shares.

Scatter plots are then created to examine the relationship between the CSAD and the return on the market as well as for the relationship between the CSAD and the average liquidity for the entire sample period. This allows for the confirmation of the relationships observed in the regression analysis discussed above.

3.4 ROBUSTNESS TESTS

As a test of robustness regarding the results of the herding behaviour regressions, this study compares the results of the regressions by changing how the market return is measured. The core methodology as described in Section 3.2 measured the market return as the arithmetic average of the natural log returns for each share for each period t. To test the robustness of the results this study runs the regressions using the natural log returns of the J203 index. Due to this research including only shares that have continuously traded during the sample period, including this measure (the 203 index) to proxy for the market return allows for the broader measure of the market return.

A further robustness test is performed regarding the relative level of market liquidity. As described in Section 3.2, the liquidity quartiles are determined relative to the distribution of market liquidity observations over the whole sample period. This robustness test will measure the distribution of market liquidity observations for each sub-period when performing the regression of Equation 11. This allows for the influence of naturally higher market liquidity later in the sample period to be minimised.

4 RESULTS

4.1 MARKET RETURNS AND RETURN DISPERSION

Table 1 below presents the descriptive statistics for the market return and the CSAD for the sample of shares over the sample period. Table 2 presents the autocorrelations for the market return and the CSAD over lags ranging from 1 day to 20 days as well as the results of the Augmented Dickey-Fuller test (ADF).

Table 1: Descriptive statistics

Statistics	Market return	CSAD
Observations	5495	5495
Mean	0.0003	0.0145
Standard deviation	0.0101	0.0056
Minimum	-0.1070	0.0049
Maximum	0.0636	0.0829
Range	0.1706	0.0780
Standard error	0.0001	0.0001
Skewness	-0.8783	2.7616
Kurtosis	9.3764	17.0732

Note: Table reports the descriptive statistics for (1) the market return which is the equally weighted average of the individual share returns; and (2) the cross absolute standard deviation (CSAD) for the sample period January 2000 to December 2021 measured as $CSAD_t = \frac{\sum_{i=1}^{N}|R_{i,t}-R_{m,t}|}{N}$, where $R_{i,t}$ is the observed return of share i at time t, $R_{m,t}$ is the market return at time t, and N is the number of shares

Table 2: Serial correlation and unit root tests

Market return		CSAD	
Panel A		Panel B	
Lags		Lags	
1	0.089	1	0.698
2	0.015	2	0.658
3	0.017	3	0.631
4	0.003	4	0.606
5	0.025	5	0.601
10	0.011	10	0.568
20	0.012	20	0.506
ADF test			
t-stat	-49.673***	t-stat	-20.418***

Note: The table reports the serial correlation for the market return measure and the CSAD measure. Also reported is the test statistics for the Augmented Dickey-Fuller test.
*** Denotes statistical significant at the 1% level.

Table 1 shows that the average daily return of the market was 0.0003. Further, the maximum daily return experienced was 0.0636 and the minimum daily return was -0.107. Panel A of Table 2 shows that there is low autocorrelation for the market return and the various number of lags. Panel B shows that CSAD is highly autocorrelated. Therefore, in order to account for the high level of autocorrelation and heteroscedasticity the regressions conducted employ the methodology of Newey and West (1987). Lastly, the results of the ADF test-statistic (statistically significant at the 1% level) indicate that the market return and CSAD daily time series are stationary.

4.2 AMIHUD'S LIQUIDITY AND HERDING BEHAVIOUR RESULTS

This section presents the pertinent results of the herding behaviour and equity market liquidity regressions by employing the three measures of liquidity. Table 3 presents the results of running the regression in equation 8 over the five periods. Each row represents the dependent variables in the regression with β, γ, and α representing the absolute value of the market return, the market return squared, and the constant, respectively. The columns of the table represent the five sub-periods.

Table 3: Herding behaviour

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β	0.359***	0.315***	0.205**	0.101**	0.584***
	(0.058)	(0.036)	(0.082)	(0.044)	(0.100)
γ	2.190**	1.042	4.438*	10.289***	-1.174
	(1.072)	(1.073)	(2.361)	(2.540)	(1.395)
α	0.012***	0.012***	0.016***	0.012***	0.014***
	(0.0003)	(0.0002)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 8

* p-value<0.1;
** p-value <0.05;
*** p-value <0.01

Table 3 presents no evidence of herding behaviour during any of the five periods. The only period that presents a negative γ coefficient (evidence in favour of herding behaviour) is the Covid-19 sub-period; however, this result is not statistically significant. The Whole Period presents a statistically positive γ coefficient which indicates evidence in favour of increased individuality regarding the trading behaviour of the market. This result is consistent with the

Crisis sub-period (significant at the 10% level) and the post-crisis sub-period. Overall, with the exception of the Covid-19 sub-period, all periods present evidence that is inconsistent with the notion of herding behaviour. This finding is consistent with Galariotis et al. (2016) which found no evidence of herding behaviour for France, Japan, the UK, the US, and Germany (only exception being Germany during the Crisis period). This is also consistent with Indars, Savin, and Lubloy (2019) which found that investors in the Moscow Stock Exchange did not display evidence of herding behaviour during the full sample period. Finally, this observation is also consistent with BenSaida, Jlassi, and Litimi (2015) which found no evidence of herding behaviour in the S&P 500 and DJIA market during the sample period.

Table 4 presents the results of running the regression in Equation 11 over the five periods. Each row represents the dependent variables in the regression with β_0, β_1, β_2, β_3, and α representing the absolute value of the market return, the squared market return squared, the squared market return if liquidity fell in the upper quartile of liquidity, the market return squared if liquidity fell in the lower quartile of liquidity, and the constant, respectively.

Table 4: Herding behaviour and liquidity

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.326***	0.389***	0.206***	0.105**	0.494***
	(0.031)	(0.041)	(0.063)	(0.044)	(0.124)
β_1	4.761***	-7.281***	5.526***	8.812***	1.737
	(0.832)	(2.126)	(1.980)	(2.085)	(2.114)
β_2	-4.220*	-34.868***	-19.988***	2.982	-14.843***
	(2.353)	(7.669)	(4.251)	(1.948)	(5.302)
β_3	-3.087***	8.395***	-2.775**	0.979	-2.630**
	(0.760)	(2.154)	(1.257)	(1.649)	(1.338)
α	0.012***	0.012***	0.016***	0.012***	0.015***
	(0.0002)	(0.0002)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured by Amihud's measure of liquidity.
* p-value<0.1;
** p-value <0.05;
*** p-value <0.01

Table 4 presents interesting results regarding the relationship between herding behaviour and liquidity. For the majority of the time periods analysed there is evidence of herding behaviour when conditioned on the level of liquidity. This is seen though the statistically negative upper and lower liquidity quartile coefficients. Therefore, consistent with previous studies (Chang et al., 2000; Chiang & Zheng, 2010; Galariotis et al.,2016), investors tend to herd only occasionally.

For the whole sample period, the crisis, and covid-19 sub-periods the liquidity quartile coefficients are statistically negative for both the upper and the lower quartiles which is evidence of herding behaviour. However, the size of the coefficients for the upper liquidity quartiles are larger than the lower liquidity quartiles. This implies that the market's reaction to news is asymmetric. These results imply at as the level of market liquidity increases there is a tendency for investors to increase their level of herding around the mean.

However, the results for the pre-crisis sub-period indicate herding behaviour in the upper liquidity quartile whereas the lower liquidity quartile displays a statistically positive coefficient which is evidence of increased return dispersion (increased individuality). During this period, as one moves from the lower liquidity quartile to the upper quartile the sign of the coefficient changes from positive to negative (both statistically significant) which indicates that as market liquidity increases from the lower quartile to the upper quartile investors begin to decrease their level of individuality and begin to display herding behaviour. Lastly, the post-crisis sub-period presents no evidence of herding behaviour regardless of the liquidity quartile and instead presents a positive liquidity quartile coefficient for both liquidity quartiles.

The results of Table 4 present some evidence of the relationship between the level of liquidity and herding behaviour. Analysis of the whole sample period does not seem to imply that greater liquidity induces herding behaviour. Instead, it appears that greater liquidity induces *more* herding behaviour (whether this result is due to fundamental or non-fundamental information is beyond the scope of this study). This can be seen in Figure 1 below which plots CSAD versus Amihud's measure of liquidity.

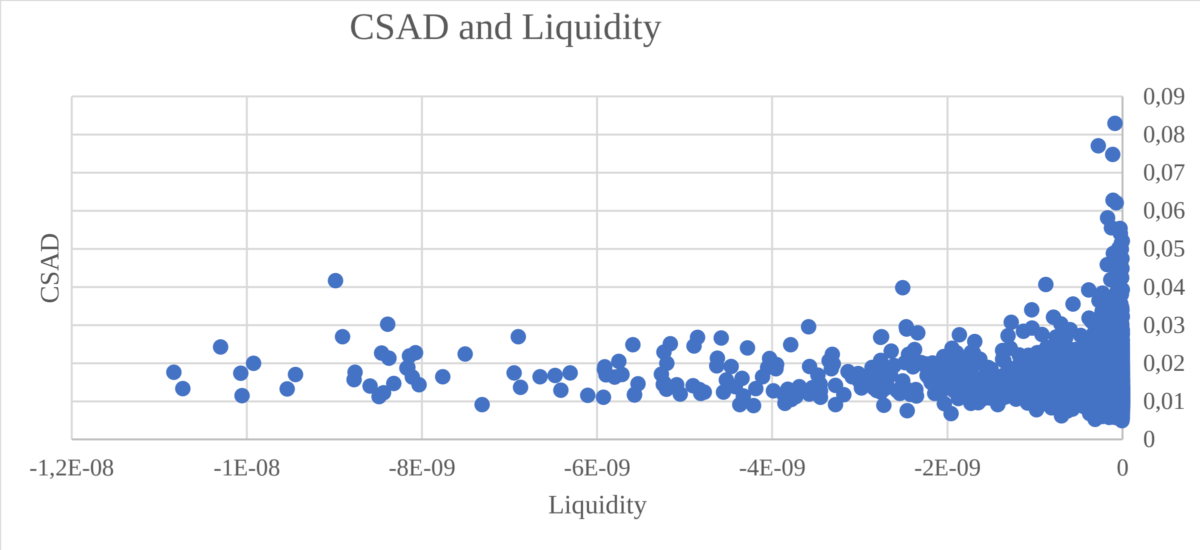

Figure 1: Plots CSAD vs Amihud's measure of liquidity over the whole sample period

Figure 1 appears to confirm the results of Table 4: return dispersion is relatively low (herding towards the mean) at both low and high levels of market liquidity. The finding of asymmetric herding behaviour patterns is consistent with many studies (Tan et al., 2008; Gavriilidis et al., 2013; Lam & Qiao, 2015; Galariotis et al., 2016). However, evidence of herding behaviour in both the lower and upper liquidity observations is inconsistent with Galariotis et al. (2016) which showed a clear negative relationship between the level of liquidity and return dispersion i.e., an increase in liquidity was associated with herding towards the market consensus. Specifically, for the majority of the time periods and countries analysed, the authors presented a statistically positive lower liquidity quartile coefficient and a statistically negative upper liquidity quartile coefficient. The only sub-period which was consistent with Galariotis et al. (2016) was the pre-crisis sub-period. Another interesting finding in contrast to Galariotis et al. (2016) is that where the authors demonstrated no evidence of herding behaviour in the lower liquidity quartile, the findings above present statistically negative lower liquidity coefficients for two of the four sub-periods and for the sample period as a whole.

Therefore, it seems that regarding the finding of herding behaviour in higher market liquidity periods, the JSE displays characteristics consistent with larger and more developed equity markets (such as the UK and the USA). However, there appears to be an observable difference between developed and developing equity markets regarding the relationship between liquidity and herding behaviour. Specifically, the finding of herding behaviour in the lower liquidity observations. Overall, it appears that a tendency for investors to herd around the mean given an increase in liquidity may not be entirely accurate for the JSE (only true for the pre-crisis sub-period). Instead, an increase in liquidity is associated with an *increased* tendency to herd around the mean. However, this observation is dependent on the time period.

4.3 EFFECTIVE BID-ASK SPREAD AND HERDING BEHAVIOUR

Since there is not one best measure of liquidity this section presents the regression results with liquidity measured as the percentage effective bid-ask spread. Table 5 shows the results of the regression of Equation 11 with the percentage effective bid-ask spread as the measure of liquidity as measured in Equation 12.

Table 5: Herding behaviour and the percentage bid-ask spread.

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.382***	0.388***	0.298***	0.102**	0.688***
	(0.055)	(0.043)	(0.097)	(0.043)	(0.151)
β_1	0.977	-10.020***	-6.100	10.144***	-3.096*
	(0.968)	(3.147)	(3.942)	(2.978)	(1.849)
β_2	-4.343**			-0.543	-13.981**
	(1.773)			(2.340)	(5.517)
β_3	2.049**	10.880***	8.876***	5.476*	2.198*
	(0.819)	(2.684)	(2.343)	(3.219)	(1.203)
α	0.012***	0.012***	0.015***	0.012***	0.014***
	(0.0003)	(0.0003)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured as the percentage effective bid-ask spread
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

Firstly, it is important to note that due to the methodology of determining the liquidity quartiles over the entire sample period the pre-crisis and crisis sub-periods do not have observations that fall within the upper quartile of liquidity when measured as the percentage effective bid-ask spread. Table 5 above presents some contrasting findings compared to Table 4. The results for the whole sample period present evidence of herding behaviour in the upper liquidity quartile (a finding consistent with Table 4) and evidence of increased individuality in the lower liquidity quartile (a finding inconsistent with Table 4). This result is consistent with Galariotis et al. (2016) which showed a statistically significant positive coefficient for the lower liquidity quartile and a statistically significant negative coefficient for the upper liquidity quartile for all G5 countries. Furthermore, this result is consistent in the covid-19 sub-period whereby a statistically positive coefficient for the lower liquidity quartile is observed as well as a statistically negative coefficient for the upper liquidity quartile.

Regarding the sub-periods, the pre-crisis and crisis sub-periods present statistically positive lower liquidity quartile coefficients. This implies evidence of increased individuality for the lower liquidity level during the pre-crisis and crisis sub-periods. For the post-crisis sub-period there is evidence of increased individuality in the lower liquidity quartile. However, the upper liquidity quartile displays a negative coefficient although not statistically significant. While not statistically significant, the negative sign of the coefficient may imply an enhancement of the level of herding behaviour since it reduces return dispersion. Overall, the results of Table 5 display the asymmetric effect of liquidity on herding behaviour.

When one considers the sample period as a whole, Amihud's measure of liquidity showed evidence of herding behaviour for both liquidity quartile, however, with a greater level of herding in the upper liquidity quartile whereas the effective percentage bid-ask spread measure of liquidity shows a change of increased individuality in the lower liquidity quartile and herding behaviour in the upper liquidity quartile. Therefore, both measures are consistent with the ideas of asymmetric herding behaviour as well as that increased liquidity tends to be associated with greater herding behaviour. The major difference observed is the strength of the relationship between liquidity and herding behaviour. This relationship appears to be stronger when liquidity is measured as the percentage effective bid-ask spread compared to Amihud's liquidity measure. This relationship can be seen in Figure 2 below which plots CSAD versus the percentage effective bid-ask spread.

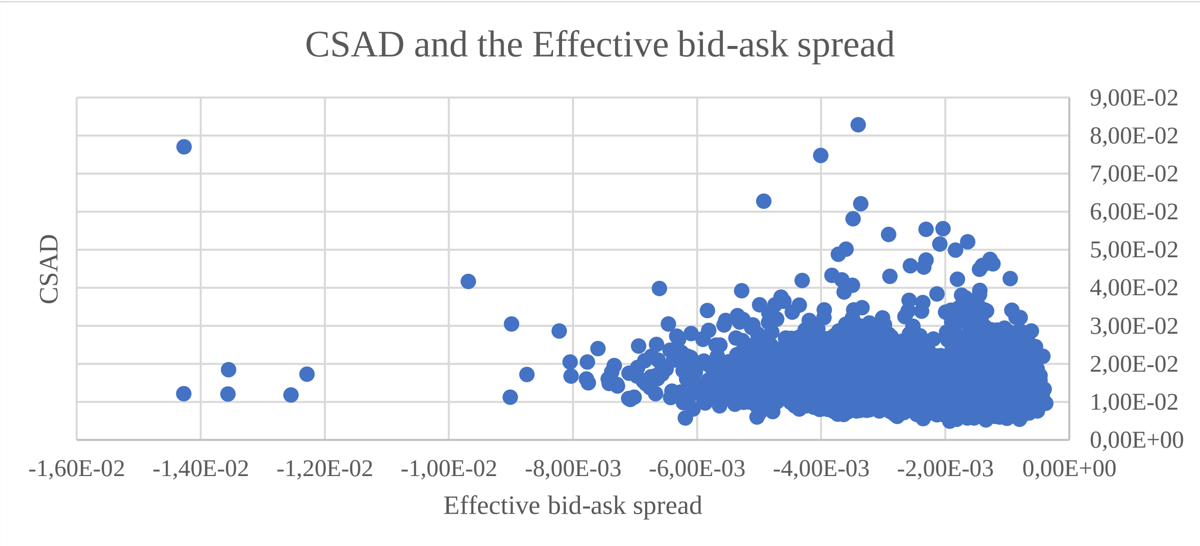

Figure 2: CSAD versus the effective bid-ask spread.

Figure 2 above appears to display a significantly more negative relationship between liquidity and herding behaviour compared to Figure 1 (Amihud's measure of liquidity). Specifically, Figure 2 confirms the results of Table 5: an increase in the level of equity market liquidity appears to induce herding behaviour. When one compares the results of Amihud's measure of liquidity and the effective bid-ask spread, both measures of liquidity show that herding behaviour can be identified when conditioned on liquidity. Similarly, both measures suggest an asymmetric nature of liquidity and its relationship to herding behaviour. At the core of the results for each measure, a consistency that one may infer is that increasing the level of market liquidity induces a greater level of herding behaviour.

4.4 TURNOVER AND HERDING BEHAVIOUR

Consistent with Section 1.3 this section presents the regression results with liquidity measured as turnover. Table 6 shows the results of the regression of Equation 11with the turnover as the measure of liquidity as measured in Equation 13.

Table 6: Herding behaviour and turnover

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.421***	0.365***	0.202**	0.181***	0.750***
	(0.074)	(0.041)	(0.090)	(0.048)	(0.115)
β_1	-4.649	-3.461**	5.505*	2.170	-22.823***
	(2.986)	(1.549)	(3.134)	(2.498)	(4.721)
β_2	6.280***	0.592	-1.152	7.202***	19.707***
	(2.070)	(1.444)	(1.676)	(1.706)	(3.676)
β_3	4.532***	5.464***	-12.685**	-5.043	-29.786***
	(1.697)	(1.787)	(5.582)	(5.763)	(5.740)
α	0.012***	0.012***	0.016***	0.011***	0.014***
	(0.0003)	(0.0002)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured through turnover.
* p-value<0.1;
** p-value <0.05;
*** p-value <0.01

Table 6 presents rather contrasting evidence compared to the results seen in Table 4 and Table 5. There are no statistically significant negative liquidity coefficients for the whole period regression. Instead, Table 6 presents statistically significant evidence of increased individuality for the upper and lower liquidity quartile. Therefore, despite conditioning on liquidity, there is no evidence of herding behaviour. This is contrasted against Table 4 which presented statistically negative coefficients for the upper and lower liquidity quartiles and Table 5 which presented evidence of a statistically positive coefficient for the lower liquidity quartile and a statistically negative coefficient for the upper liquidity quartile. This result appears to imply an increased level of individuality regardless of the level of liquidity.

For the pre-crisis sub-period, Table 6 displays evidence inconsistent with herding behaviour for the lower liquidity quartile. However, a statistically significant positive coefficient for the lower liquidity quartile for the pre-crisis sub-period is consistent across all three measures of liquidity. Furthermore, in contrast to Table 4, which presented significant evidence of herding behaviour in the upper liquidity quartile, Table 5 presents a positive, although statistically insignificant, liquidity coefficient.

The lower liquidity quartile coefficient is negative and statistically significant for the crisis sub-period, which is evidence of herding behaviour. The sign of the upper liquidity quartile coefficient remains negative although statistically insignificant. For the post-crisis sub-period, the upper liquidity quartile presents a statistically significant positive coefficient which is evidence of increased individuality. The lower liquidity quartile presents a negative and statistically insignificant coefficient. Finally, for the covid-19 sub-period, the lower liquidity quartile presents statistically significant evidence of herding behaviour in the upper liquidity quartile and statistically significant evidence of increased individuality (increased return dispersion) in the lower liquidity quartile.

The results of Table 6 appear to present an opposite relationship between liquidity and herding behaviour when measured as turnover compared to when liquidity is measured through Amihud's measure of liquidity, and the effective percentage bid-ask spread. The implication of the results of Table 6 seems to be that there is a positive relationship between liquidity and return dispersion (increased individuality). Specifically, as the level of market liquidity increases the level of individuality (return dispersion) increases. This can be seen in Figure 3 below which plots CSAD versus turnover:

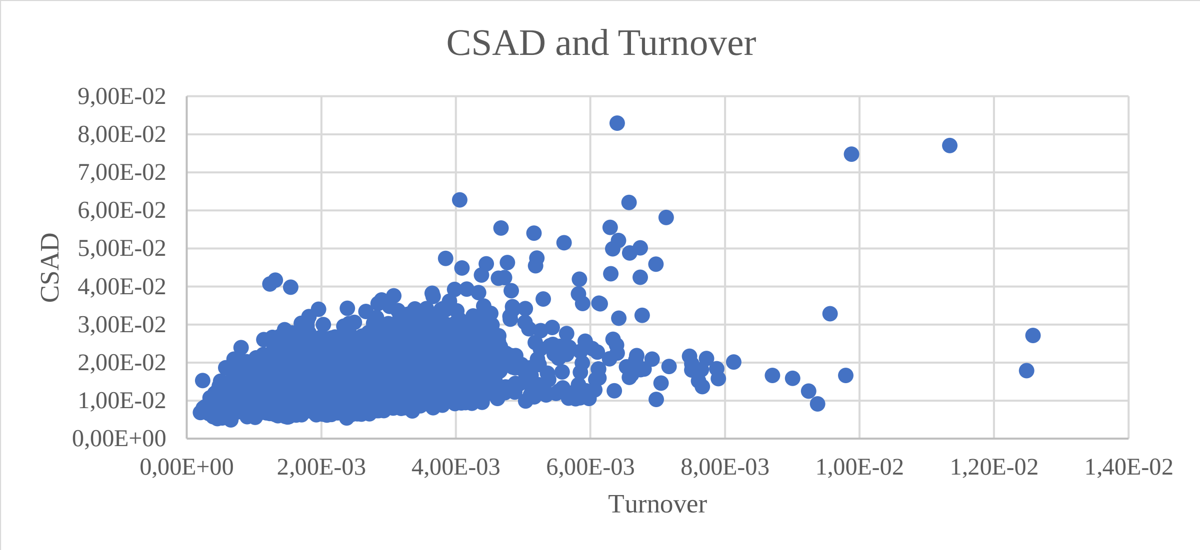

Figure 3: Plot of CSAD and turnover

In Figure 3 above, the positive relationship mentioned above appears to be present. That is, as the level of liquidity increases the level of return dispersion increases (increased individuality). However, evidence of herding behaviour in the lower liquidity quartile appears to be dependent on the time period investigated since the whole sample period and the pre-crisis sub-period indicated evidence of increased individuality whereas the crisis and covid-19 sub-periods indicated evidence of herding behaviour for the lower liquidity quartiles. Turnover seems to produce an opposite relationship of liquidity and herding behaviour compared to Amihud's measure of liquidity and the effective percentage bid-ask spread as liquidity increases there is a tendency for investors to increase their deviation from the mean.

5 ROBUSTNESS RESULTS

This section presents the results of the two robustness tests employed: altering the proxy for market return and measuring the relative level of liquidity in the sub-period analysed.

5.1 ALTERNATIVE MEASURE OF MARKET RETURN

As a robustness test to the results, this section presents the regression results when the return on the market is measured as the natural log return of the J203. Table 7 below presents the results of the regressions of Equation 11:

Table 7: Herding behaviour with alternative market return proxy.

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β	0.287^{***}	0.296^{***}	0.229^{***}	0.149^{***}	0.567^{***}
	(0.033)	(0.044)	(0.063)	(0.035)	(0.136)
γ	2.928^{***}	2.109	2.788^{***}	4.139^{***}	-0.767
	(0.770)	(1.635)	(0.939)	(1.437)	(1.997)
α	0.012^{***}	0.012^{***}	0.016^{***}	0.012^{***}	0.016^{***}
	(0.0002)	(0.0003)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 8 with the market return proxied with the natural log return of the J203 Index.
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

The results of Table 7 above are identical to the results in Table 3: there is no evidence to support the notion of herding behaviour. For the majority of the time periods investigated there is a positive and statistically significant coefficient which is evidence against the notion of herding behaviour (with the exception of the pre-crisis sub-period which presented a statistically insignificant yet positive coefficient). Table 8 below presents the results of Equation 11 when liquidity is measured through Equation 9 (Amihud's measure of liquidity):

Table 8: Herding behaviour and liquidity with J203 to proxy for the market return.

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.307^{***}	0.348^{***}	0.245^{***}	0.151^{***}	0.433^{***}
	(0.027)	(0.044)	(0.055)	(0.035)	(0.144)
β_1	3.266^{***}	-3.386^{***}	3.043^{***}	4.003^{***}	4.910^{*}
	(0.690)	(1.243)	(0.647)	(1.505)	(2.739)
β_2	-7.028^{***}	-9.409^{**}	-7.049^{***}	-0.201	-18.041^{***}
	(1.349)	(4.436)	(2.280)	(1.284)	(5.490)
β_3	-0.944	5.632^{***}	-1.450^{***}	0.927	-4.833^{***}
	(0.707)	(1.492)	(0.475)	(1.370)	(1.527)
α	0.012^{***}	0.012^{***}	0.016^{***}	0.012^{***}	0.017^{***}
	(0.0002)	(0.0003)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured as Amihud's measure of liquidity and the natural log of the J203 index as the proxy for the market return.
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

The results of Table 8 above are qualitatively similar to Table 4: it appears that as the level of market liquidity increases the level of herding behaviour increases. For the whole sample period, Table 8 presents evidence of herding behaviour in the upper liquidity quartile. While both Table 8 and Table 4 present a negative lower liquidity quartile coefficient, Table 8 presents a coefficient which is not significant. Therefore, for the whole sample period, regardless of the measure of market return, both tables appear to imply that as the level of market liquidity increases the level of herding behaviour increases (return dispersion decreases).

For the pre-crisis sub-period Table 8 shows a statistically significant positive coefficient for the lower liquidity quartile and a statistically significant negative coefficient for the upper liquidity quartile which is consistent with Table 4. Therefore, consistent with Table 4, Table 8 presents evidence of herding behaviour in the upper liquidity quartile and evidence of increased individuality in the lower liquidity quartile. For the crisis sub-period, both tables present statistically significant negative coefficients for both the upper and lower liquidity quartile, however, the absolute value of the upper liquidity coefficient is larger than the lower liquidity coefficient. This implies a greater level of herding behaviour when market liquidity is greater. The post-crisis sub-period presents statistically insignificant coefficients for both Table 8 and Table 4. However, the negative upper liquidity coefficient and the positive lower liquidity coefficient implies that increasing the level of liquidity decreases the level of herding dispersion. Lastly, for the covid-19 sub-period both Table 8 and Table 4 present statistically negative liquidity quartile coefficients for both liquidity quartiles with the absolute value of the upper liquidity quartile being larger than the lower liquidity quartile.

Table 8 and Table 4 present virtually the same results and in general, regardless of the proxy for the market return, both tables show evidence of a greater level herding behaviour for a greater level of market liquidity. Therefore, when one uses Amihud's measure of liquidity in testing for herding behaviour, the proxy for market return does not appear to change the results significantly.

Table 9 below presents the results when liquidity is measured through the effective percentage bid-ask spread:

Table 9: Herding behaviour and liquidity (Effective bid-ask spread) with J203 to proxy for the market return.

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.320***	0.371***	0.280***	0.155***	0.766***
	(0.032)	(0.044)	(0.068)	(0.037)	(0.193)
β_1	0.783	-6.476***	-1.270	2.467*	-4.135*
	(0.634)	(1.777)	(2.031)	(1.391)	(2.281)
β_2	-3.122*			2.539*	-22.202***
	(1.744)			(1.411)	(6.477)
β_3	2.395***	7.937***	3.431**	7.186***	2.598***
	(0.721)	(1.388)	(1.362)	(1.644)	(0.911)
α	0.012***	0.012***	0.016***	0.012***	0.016***
	(0.0002)	(0.0003)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured through the effective bid-ask spread and the natural log of the J203 index as the proxy for the market return.
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

The results of Table 9 above are qualitatively similar to Table 5. Firstly, both tables present evidence of increased individuality in the lower liquidity quartile and evidence of herding behaviour in the upper liquidity quartile for the whole sample period. Secondly, both tables present evidence of increased individuality in the lower liquidity quartile for the pre-crisis and crisis sub-periods with no observations in the upper liquidity quartile. Lastly, both tables present evidence of increased individuality in the lower liquidity quartile for the covid-19 sub-period as well as evidence of herding behaviour for the upper liquidity quartile. The only difference is presented in the post-crisis period where Table 9 presents a statistically significant positive upper liquidity coefficient, Table 5 presented a statistically insignificant negative upper liquidity coefficient. However, both tables present evidence of increased individuality for the lower liquidity quartile for this sub-period.

Therefore, the results imply that regardless of the proxy used for the market return, in general when liquidity is measured as the effective percentage bid-ask spread, a higher level of liquidity is associated with a lower return dispersion and a lower level of liquidity is associated with a higher level of return dispersion.

Table 10 below presents the results when liquidity is measured through turnover:

Table 10: Herding behaviour and liquidity (turnover) with J203 to proxy for the market return.

	Whole Period	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.319***	0.290***	0.232***	0.188***	0.852***
	(0.051)	(0.048)	(0.071)	(0.039)	(0.172)
β_1	0.547	2.469	3.077*	0.429	-28.934***
	(1.743)	(2.277)	(1.623)	(1.670)	(6.660)
β_2	2.268*	-1.865	-0.384	4.323***	24.766***
	(1.352)	(1.267)	(0.952)	(1.179)	(4.852)
β_3	1.000	0.718	-7.147*	-4.892*	-15.806***
	(1.076)	(1.775)	(3.887)	(2.817)	(5.730)
α	0.012***	0.012***	0.016***	0.012***	0.015***
	(0.0003)	(0.0003)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured through turnover and the natural log of the J203 index as the proxy for the market return.
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

Table 10 above appears to present many similarities to Table 6 with some differences. Firstly, for the whole sample period Table 10 presents evidence of increased individuality for the upper liquidity quartile (at the 10% level) which is consistent with Table 6. The difference being that Table 6 presented a statistically significant positive coefficient for the lower liquidity quartile. However, the core result is consistent with Table 6 that a higher level of liquidity is associated with a greater level of return dispersion.

The results for the pre-crisis sub-period between the two tables are slightly inconsistent. Table 10 does not present a statistically significant coefficient for the lower liquidity quartile while Table 6 presented a positive statistically significant term. Furthermore, while both tables present statistically insignificant coefficients for the upper liquidity quartile, Table 10 presents a negative sign whereas Table 6 presented a positive sign. However, one can argue that the core relationship displayed is consistent. That is, as one moves from a lower level of liquidity to a higher, the amount of return dispersion decreases.

The results for the crisis sub-period are consistent with a negative statistically significant coefficient for the lower liquidity quartile and a negative statistically insignificant upper liquidity quartile coefficient. Therefore, as the level of liquidity decreases the level of return dispersion increases. For the post-crisis and covid-19 sub-periods, both tables present evidence of increased individuality in the upper liquidity quartile and evidence of herding behaviour in the lower liquidity quartile.

In general, the implications for each measure of liquidity appear to hold regardless of the market return proxy. For Amihud's measure of liquidity, a greater level of liquidity was associated with a greater level of herding behaviour. For the effective percentage bid-ask spread, increases in the level of liquidity were associated with inducing herding behaviour. And for turnover, an increase in the level of liquidity was associated with an increase in individuality.

5.2 SUB-PERIOD LIQUIDITY QUARTILES

One can argue that over time an equity market's level of liquidity naturally increases. Furthermore, this may be especially true for developing equity markets. Therefore, the methodology of this study regarding the approach to measuring liquidity quartiles may not be entirely accurate since the level of liquidity towards the end of the sample period should be naturally larger than the beginning of the sample period. This can be seen in Figure 4 and Figure 5 below which plots the measures of liquidity over the sample period.

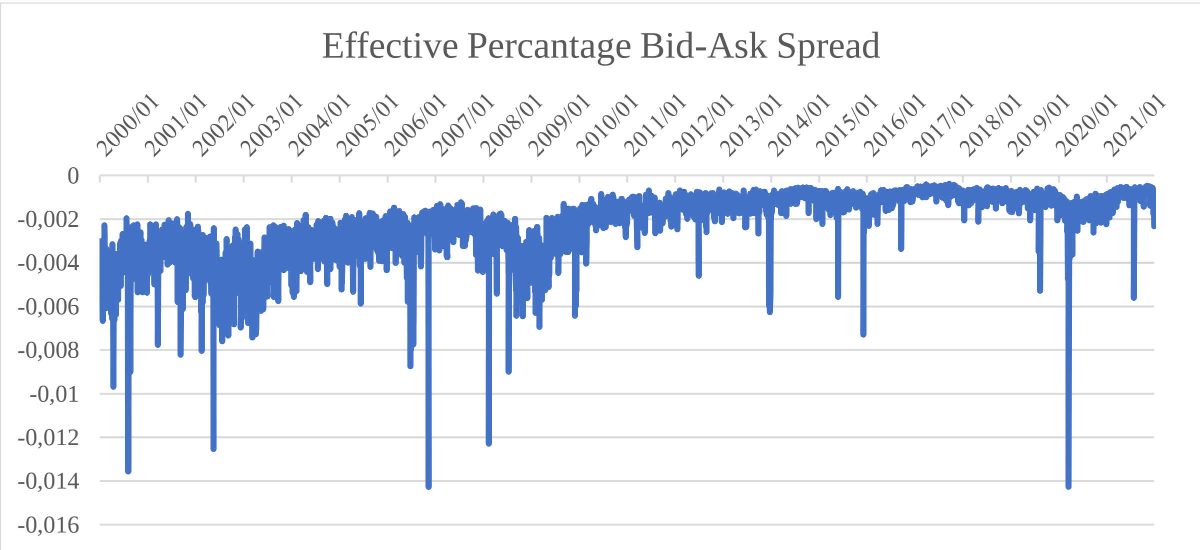

Figure 4: The effective percentage bid-ask spread over the sample period.

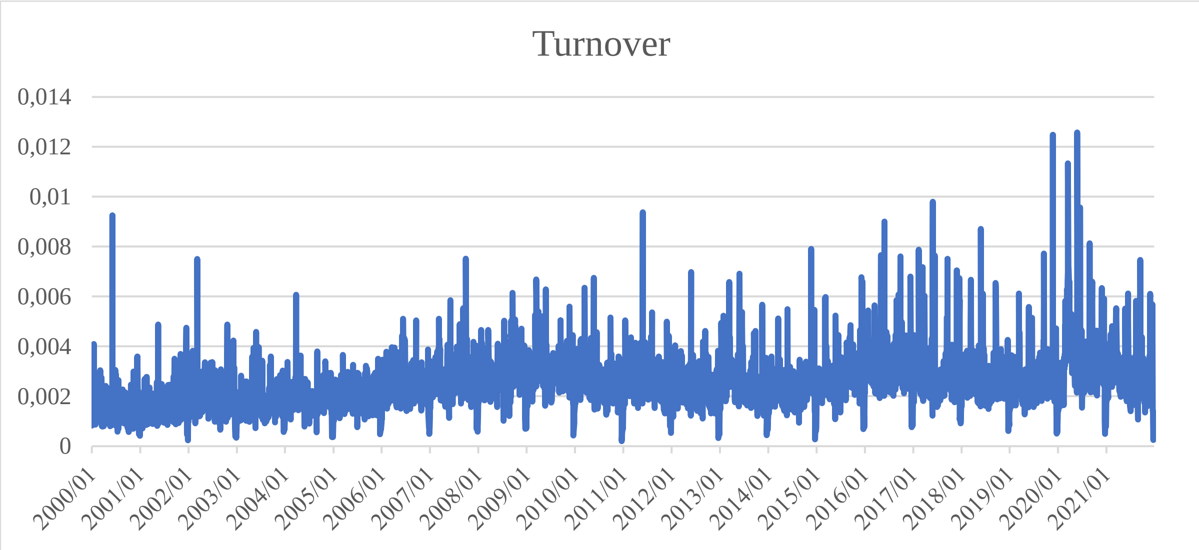

Figure 5: Turnover over the whole sample period

Qualitatively, there is evidence of a natural trend of the level of liquidity increasing over time. Therefore, it is prudent to run the regressions again with an updated method of determining which quartile the market's level of liquidity falls into. Initially this study determined the liquidity quartiles over the entire sample period which led to the effective percentage bid-ask spread measure of liquidity not having any observations in the upper liquidity quartile for particular sub-periods. Moreover, measuring an observation's level of liquidity against the distribution of all observations introduces a forward-looking bias. Consider this, a day t level of liquidity may be considered low when it is compared against the average level of liquidity of the entire sample period because this distribution includes observations of liquidity from the future which naturally trend upwards. However, from the perspective of the market on day t, the level of market liquidity may have been average or high. This study addresses this by presenting the results of the regressions whereby the liquidity quartiles are determined for each sub-period instead of over the whole sample period.

As mentioned above, this section runs the regression in equation 11 over the four sub-periods periods for each measure of liquidity. Each row represents the dependent variables in the regression with β_0, β_1, β_2, β_3, and α representing the absolute value of the market return, the squared market return, the squared market return if liquidity fell in the upper quartile of liquidity, the squared market return if liquidity fell in the lower quartile of liquidity, and the constant, respectively. Table 11 below presents the results of Amihud's measure of liquidity.

Table 11: Herding behaviour and Amihud's measure of liquidity with liquidity quartiles measured relative to each sub-period.

	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.415***	0.196***	0.101**	0.647***
	(0.054)	(0.063)	(0.045)	(0.129)
β_1	-3.719*	5.768***	10.640***	-2.962
	(2.036)	(1.916)	(2.901)	(3.100)
β_2	-6.390*	-0.994	1.406	-17.372***
	(3.469)	(2.221)	(2.306)	(5.375)
β_3	5.524***	-2.721**	-2.315	1.098
	(1.373)	(1.265)	(2.066)	(2.310)
α	0.012***	0.016***	0.012***	0.014***
	(0.0003)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured as Amihud's measure of liquidity with the liquidity quartiles determined relative to each sub-period.
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

The results of Table 11 present evidence that the base at which one measures the relative level of liquidity is important and can change whether evidence of herding behaviour is detected in various sub-periods. The pre-crisis sub-period presents evidence of increased individuality for the lower liquidity quartile and evidence of herding behaviour for the upper liquidity quartile (significant at the 10% level) which is consistent with the results of Table 4 for this sub-period.

For the crisis sub-period, Table 11 presents a negative statistically significant coefficient for the lower liquidity quartile which is consistent with Table 4. However, the negative and insignificant upper liquidity coefficient is not consistent with Table 4 which had a negative statistically significant coefficient which was larger in absolute value compared to the lower liquidity quartile coefficient. Therefore, where Table 4 presented evidence of decreased return dispersion as liquidity increased, when the level of liquidity is measured relative to the liquidity during the crisis sub-period there is evidence that as liquidity decreases return dispersion decreases.

For the post-crisis sub-period, neither liquidity quartile coefficients are statistically significant, which is consistent with Table 4. However, the sign of the lower liquidity quartile coefficient is not consistent with the sign in Table 4. Therefore, when liquidity is measured relative to the level of liquidity during the post-crisis sub-period, the lower quartile of liquidity shows a decrease in return dispersion.

Lastly, for the covid-19 sub-period, Table 11 presents a negative statistically significant upper liquidity quartile coefficient which is consistent with Table 4. However, the positive statistically insignificant lower liquidity quartile coefficient is not consistent with the negative statistically significant coefficient.

In general, Table 11 and Table 4 both show evidence that as the level of liquidity increases the level of herding behaviour increases for the pre-crisis and covid-19 sub-periods. The crisis sub-period appears to imply that as liquidity decreases the level of herding behaviour increases, which is the opposite relationship seen in Table 4. For the post-crisis sub-period, Table 11 above implies that return dispersion increases as liquidity increases, which is consistent with Table 4. Therefore, based on the results above one can argue that the relationship between liquidity and herding behaviour is dependent on the time period whereby one may see the relationship being the opposite from one time period to the next.

Table 12 below presents the results of the effective percentage bid-ask spread measure of liquidity:

Table 12: Herding behaviour and the effective bid-ask spread with liquidity quartiles measured relative to each sub-period.

	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.402^{***}	0.313^{***}	0.100^{**}	0.794^{***}
	(0.041)	(0.099)	(0.045)	(0.141)
β_1	-1.504	-0.535	10.709^{***}	-13.957^{***}
	(1.825)	(3.766)	(2.870)	(4.874)
β_2	-14.497^{***}	-14.450^{***}	-0.171	-15.869^{***}
	(3.040)	(5.075)	(1.846)	(5.003)
β_3	1.829	3.186	-0.870	10.441^{***}
	(1.751)	(2.122)	(2.369)	(3.550)
α	0.012^{***}	0.015^{***}	0.012^{***}	0.014^{***}
	(0.0003)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured as the effective bid-ask spread with the liquidity quartiles determined relative to each sub-period.
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

Table 12 above presents negative statistically significant upper liquidity coefficients which is evidence of herding behaviour for the pre-crisis, crisis, and Covid-19 sub-period. The coefficients of the lower liquidity quartiles are positive although not statistically significant with the exception of the Covid-19 sub-period. . Therefore, for the pre-crisis, crisis, and Covid-19 sub-periods, Table 12 implies that as the level of market liquidity increases there is a tendency for the market to herd.

The post-crisis sub-period presents negative and statistically insignificant liquidity coefficients for both liquidity quartiles. However, while not statistically significant, it appears that the amount of return dispersion is greater at the lower liquidity quartile which is the opposite to Table 5 which showed that return dispersion significantly increases at the lower liquidity quartile.

Therefore, one can conclude that for the majority of the time periods an increase in liquidity was associated with a tendency for the market to herd around the mean. This is consistent with the full sample period finding.

Table 13 below presents the results of the turnover measure of liquidity:

Table 13: Herding behaviour and turnover with liquidity quartiles measured relative to each sub-period.

	Pre-crisis	Crisis	Post-crisis	Covid-19
β_0	0.320***	0.195**	0.193***	0.806***
	(0.040)	(0.093)	(0.049)	(0.129)
β_1	3.384*	5.188*	2.642	-18.682***
	(2.046)	(2.914)	(2.497)	(4.958)
β_2	-5.532***	-0.713	6.528***	15.001***
	(1.589)	(1.586)	(1.717)	(3.810)
β_3	-1.598	-1.353	-6.809	-25.862***
	(2.311)	(3.650)	(4.941)	(6.028)
α	0.012***	0.016***	0.011***	0.014***
	(0.0002)	(0.001)	(0.0003)	(0.001)

Note: The table reports the results of the regression of Equation 11 with liquidity measured through turnover with the liquidity quartiles determined relative to each sub-period.
* p-value<0.1;
**p-value <0.05;
***p-value <0.01

For the pre-crisis sub-period, Table 13 above presents evidence of herding behaviour in the upper liquidity quartile for the pre-crisis sub-period and a less negative although statistically insignificant coefficient for the lower liquidity quartile. Table 6 presented evidence of increased individuality for the lower liquidity quartile and a statistically insignificant positive coefficient for the upper liquidity quartile. Therefore, for turnover the relative base at which the level of liquidity is measured against is important for the pre-crisis sub-period.

For the crisis sub-period, Table 13 presents negative statistically insignificant liquidity quartile coefficients. This is consistent with Table 6; however, Table 6 indicated a statistically significant lower liquidity coefficient. Although both tables appear to suggest a greater decrease in return dispersion at the lower liquidity quartile.

For the post-crisis sub-period, Table 13 above presents a statistically significant positive coefficient for the upper liquidity quartile and a negative but insignificant coefficient for the lower liquidity quartile which is consistent with the results observed in Table 6. This consistency is also seen for the covid-19 sub-period with evidence of herding behaviour in the lower liquidity quartile and evidence of increased individuality in the upper liquidity quartile. Therefore, for these two sub-periods the relative level of liquidity is not important.

5.3 ROBUSTNESS TESTS DISCUSSION

The results of the robustness testing regarding the proxy of the market return appear to show that the choice of market return proxy does not significantly change or influence the results. Comparing the relative level of liquidity is measure against the sub-period analysed (the robustness method) to the whole sample period (the whole sample method) produced some interesting results regarding the relationship between liquidity and herding behaviour as well as the influence a time period has on this relationship.

For Amihud's measure of liquidity both methods produce the same results for the pre-crisis sub-period: a significant positive lower liquidity quartile coefficient and a significant negative upper liquidity quartile coefficient. This implies that for the pre-crisis sub-period an increase in liquidity was associated with an increase in the tendency of the market to herd. For the crisis sub-period, both methods presented negative coefficients for both liquidity quartiles, however, the robustness method showed a greater decrease in return dispersion in the lower liquidity quartile. For the post-crisis sub-period, both methods showed an increase in return dispersion in the upper liquidity quartile, but the robustness method showed a decrease in return dispersion in the lower liquidity quartile compared to an increase in return dispersion when the level of liquidity is measured relative to the whole sample period. For the Covid-19 sub-period, when the level of liquidity was measured relative to the whole sample period, the lower liquidity quartile indicated a significant decrease in return dispersion, but the robustness method showed a significant increase in return dispersion.

Regarding the effective percentage bid-ask spread, in the post-crisis sub-period both methods showed a decrease in return dispersion in the upper liquidity quartile, however, the whole sample method showed a significant increase in return dispersion in the lower liquidity quartile where the robustness method showed a decrease.

When liquidity is measured as turnover, in the pre-crisis sub-period the whole sample method showed a significant increase in return dispersion at the lower liquidity quartile and an increase in return dispersion at the upper liquidity quartile. However, the robustness method showed a decrease in return dispersion at the lower liquidity quartile. In the crisis sub-period, both methods showed a decrease in return dispersion at the lower liquidity quartile and upper liquidity quartile however, the whole sample method was statistically significant at the lower quartile. For the post-crisis and covid-19 sub-periods, both methods showed an increase in return dispersion at the upper liquidity quartile and a decrease in return dispersion at the lower liquidity quartile.

Therefore, the results show that the choice of the time period does play a significant role in the relationship between liquidity and herding behaviour. Furthermore, the distribution to which the level of liquidity is measured against is also significantly important in determining the relationship between liquidity and herding behaviour for the particular sub-period.

6 CONCLUSION

This study attempted to identify whether investors were more likely to herd in more liquid shares compared to less liquid or whether investors were more likely to herd in less liquid shares due to the lack of information and therefore copying the actions of others (Welch, 1996; Taylor, 2002). Overall, the results of this study appear to suggest that an increase in liquidity is associated with a tendency of investors to herd towards the market consensus (reduced return dispersions as a result of investors clustering around the mean market return), which appears to be in line with the sentiment of Welch (1996). However, this observation was dependent not only on the time period analysed but also on the proxy for liquidity. Furthermore, depending on the proxy for liquidity and the time period, herding behaviour was detected in both higher and lower liquidity quartiles.

Compared to previous papers, the core result of this research is consistent with the idea that herding occurs only occasionally (Chang et al., 2000; Chiang & Zheng, 2010; Galariotis et al.,2016). Further, the apparent positive relationship between the level of liquidity and herding behaviour is generally consistent with the findings of Galariotis et al. (2016). This appears to suggest that, with regards to herding behaviour and liquidity, the JSE functions similarly to developed stock markets. When comparing to the South African research, the results of this research are consistent with Seetharam (2013) such that herding behaviour is linked to the state of the market.

For Amihud's measure of liquidity the notion that a higher level of liquidity is associated with an increased tendency for investors to herd towards the market consensus appeared to remain true for some sub-periods regardless of the relative measure of liquidity with the exception of the crisis sub-period. Unfortunately, the effective percentage bid-ask spread measure of liquidity did not allow for a direct comparison, however, the results show a consistency between Amihud's measure of liquidity and the effective bid-ask spread with regards to the whole sample period, the pre-crisis sub-period and the covid-19 sub-period. This suggests that in general, for both measures of liquidity, an increase in liquidity is associated with an increased tendency for investors to herd. The consistency of this, however, does not hold for the crisis and post-crisis sub-periods.

As this research has shown, liquidity is necessary in the detection of herding behaviour in equity markets. Furthermore, this research has shown that the relationship between liquidity and herding behaviour is, to an extent, dependent on the measure of liquidity, the time period, and the method one uses to determine the relative level of liquidity in determining more and less liquid. This is seen through how the regression results may change depending on the measure of liquidity used as well as that the relationship between liquidity and herding in one period is not necessarily the same relationship seen in different periods. However, it is clear that higher levels of market liquidity are generally associated with an increased tendency of the market to herd.

While this study is not explicitly an investment strategy study the results may still hold value for market stakeholders such as investors and portfolio managers. This study has shown that certain identified behaviours of the market may in fact be caused by some fundamental aspect driving investment decisions. Specifically, that fundamental constraints of the market, such as liquidity, may have an influence over the level of herding behaviour. Further, the magnitude of this constraint cause and effect may vary over time. Thus, it is important for investors and fund managers to be cognizant of the relationship between liquidity and herding behaviour and the trade-off between pursing investments into shares that are less likely to display herding behaviour and their relatively lower level of liquidity.

As a caveat, one may find it difficult to argue whether liquidity is causing the herding behaviour or if herding behaviour is causing the level of liquidity. For example, BenSaida et al. (2015) showed evidence of a strong bi-directional relationship between trading volume and herding behaviour. That is, trading volume can strengthen the level of herding behaviour and herding behaviour can generate higher levels of trading volume. Consider the following thought: the use of roads by many people will eventually create traffic. Would we consider this situation as a form of herding behaviour? Did the existence of roads induce herding by drivers? Therefore, one must be cautious of the statement, “higher liquidity causes herding behaviour”. This research has shown that an increased level of market liquidity is associated with an increased tendency of the market to herd, however, one cannot deny the potential bi-directional relationship these two concepts may have on each other.

6.1 AREAS FOR FUTURE RESEARCH

This study attempted to minimise the forward-looking bias of measuring the level of liquidity relative to the whole sample period by measuring liquidity relative to the distribution of liquidity during each sub-period. The relationship between liquidity and herding behaviour for each sub-period was not necessarily robust to each method. This may be caused by the natural tendency of the level of market liquidity to trend upwards and therefore cause liquidity observations earlier in time to appear relatively less liquid compared to observations later in time. An extension of the research conducted in this study might find it beneficial to measure the level of market liquidity relative to only previous observations of liquidity through a moving-average. Further, interesting observations may present themselves depending on the length of the moving average. Such a study may present insight into the "memory" of the market regarding the relative level of market liquidity and its influence on return dispersion. Furthermore, repeatedly the constants in the regressions were statistically significant, this implies that there may be missing variables in the equations and may warrant future research.

This study did not disseminate whether the observed herding behaviour was due to fundamental or non-fundamental reasons. Specifically, the herding observed in this study may have been spurious rather than intentional. Therefore, an extension to this study may be to account for fundamental reasons for herding in order to isolate herding that is spurious. Such research will be beneficial because if one isolates when and where the market is more likely display intentional (non-fundamental) herding, the individual may be able to capitalise on a trend and close out their position before the efficiency of the market catches up with the non-fundamental trend.

Another extension to this study would be to analyse not just liquidity's influence on return dispersion but also return dispersion's influence on liquidity. If liquidity induces herding behaviour, is it also true that herding behaviour induces greater liquidity? If the latter is true, there may be a limited amount of time whereby this phenomenon exists. This research would be beneficial because it would help explain an almost "chicken and egg" type situation.

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