

EFFICIENCIES IN A LEAST DEVELOPED COUNTRY - CASE OF MALAWI

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Abstract

The neoclassical theory of Finance postulates the dominant hypothesis that markets are efficient, based on the premise that investors are perfectly rational. In addition, literature suggests that institutional investors play a controlling role in the financial system through ownership and trading of securities (Choi and Sias, 2009). However, recent studies in psychology have shown that investors have behavioral biases which induce trading patterns which violate the principles of rationality. Second, studies suggest that the trading behavior of institutional investors potentially moves prices away from fundamental values contrary to market expectations.

Our thesis hypothesized that brokers use their principalness to generate higher profits than outside investors. Brokers have been documented as more likely to engage in price manipulation. Such studies have been widely investigated in emerging and developed markets. However, it has been found that empirical evidence of price manipulation is lacking in literature. In addition, studies suggest that economic agents act irrationally due to psychological bias and heuristics in their decision making. We therefore investigate the disposition effect, the tendency by investors to sell winners too early and hold onto losers for too long. This behavior is costly for investors and there is continuing debate among researchers about its underlying causes. Finally, our research investigates institutional herding behavior. This behavioral bias has potential price impacts such as destabilization of prices.

Despite the small size of the Malawi market, illiquid stocks, few brokers and stocks, and that literature shows asymmetry of information as well as brokers' use of their power to manipulate prices, the study finds that there is no evidence of trade-based manipulation. The study also finds no evidence of herd behavior amongst institutional investors indicating that investors do not imitate the trades of others. However, the study documents some evidence that investors sell winning stocks more readily than losing stocks. This disposition effect wanes over time and does not translate into momentum trading.

Our findings contribute to the body of research that challenges market efficiency by documenting some evidence from a less developed country that is neglected in literature.

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Chapter 1

1.0 Introduction

Finance researchers have pursued the understanding of security price determination process by engaging in a wide research in the field of collective investor behavior i.e. investors as a group engage in similar behavior. The systemization of crowd behavior is in two distinctive groups, namely feedback trading and herding. Bohl and Siklos (2008) define feedback trading as tendency where investors utilise past trends in prices to base their investment decision that such trends will continue while according to Hirschleifer and Teoh (2003) herding is a behavioral similarity stemming from the interactive observation of individuals. The latter is basically following what others are doing. It derives its origins from biological phenomenon, for example in learning a new skill, one imitates what others do.

Recent research has focused on collective trading patterns namely herding and feedback trading. Both patterns are driven by behavioral and non-behavioral factors. Furthermore, such factors can leave a destabilizing effect on market prices. The source of destabilization and its implication are the issues we pursue in this thesis.

We identified gaps in the literature which we have confidence that are important to investors and regulators. Given the dominant hypothesis in neoclassical theory of Finance that markets are efficient, based on the premise that investors are perfectly rational, the first research question that we address is *whether market intermediaries engage in unfair trading practice to earn higher returns than outside investors*. Specifically, we investigate the behavioral conduct of stockbrokers in the Malawian stock market by analysing profitability differentials between principal brokers and outside investors. The misconduct of stockbrokers and price manipulation in capital markets have historically been a concern to academic researchers and policy makers. These matters have a detrimental effect on market efficiency and economic development plans of a country. For example, Guiso, Sapienza and Zingales (2008) document that retail investors shun participating in the stock market if they find it less trusting. Studies such as Aggarwal and Wu (2006), Khwaja and Mian (2005), Imişiker, Özcan and Taş (2015), Aaron, Koesrindartoto and Takashima (2020) suggest that brokers are responsible for manipulated trades and that principal brokers earn between 50-92 percent higher annual returns than outside investors. We examine the question that principal brokers engage in unfair trading practice to earn higher returns than outside investors. We thus hypothesize that brokers profitability is positively related to the degree of principalness. In order to test the hypothesis

that brokers who trade as principals earn higher profits through manipulative trading than intermediary trades, we compare their trading profits relative to outside investors. Thus, we analyze their trading pattern.

There has not been studies that focus on an empirical examination of brokerage accounts for less developed countries (LDC's hereafter). As such, this study provides potential additional insights into existing manipulative schemes and profitability differentials between market intermediaries and outside investors. Our study examines brokerage trading data, using a unique data set and so builds on and contribute to work that depict price manipulation strategies as additional examples of price stabilizing speculation. It contributes to the growing field that challenges market efficiency by exploring price manipulation (Kindleberger, 1978; Shiller, 1984; DeLong, Shleifer, Summers and Waldmann, 1990; Allen and Gale, 1992; Shleifer, 2002; Khwaja and Mian, 2005; Mei, Wu and Zhou, 2005; Aggarwal and Wu, 2006; Goldstein and Guembel, 2008).

The second issue that we investigate is *whether investors exhibit the tendency to shun crystallising losses*. We specifically examine whether investors exhibit the tendency to sell winners too early and hold onto losers for too long. There is evidence from stock markets by Odean (1998) and Shapira and Venezia (2001). In addition, theoretical studies such as Jegadeesh and Titman (1993) and Rouwenhorst (1998) explain that disposition effect justifies observed behavior such as momentum trading. Further, studies such as Grinblatt and Han (2005) argue that disposition effect is the main driver of momentum profits. It has also been documented in studies such as Heath, Huddart and Lang (1999) that investors can exploit patterns and build better portfolios. The study is of interest to the wider economy for policy makers. Given assertions by the study of Coval and Shumway (2005) that disposition effect affects prices, it therefore follows that resource allocation would be impaired. While disposition effect has been extensively studied in developed countries, there is no research study on least developed countries. We fill this gap by investigating trading records of Malawian investors between 2013 and 2019. We are not aware of any other study in least developed countries. We contribute to the body of knowledge on investor selling behavior by documenting evidence. This allows insights into disposition effect in LDCs where there is dearth of research. It has been documented that disposition effect leads to suboptimal performance (Odean (1998), Weber and Camerer (1998), and Frydman and Rangel (2014)). The findings also contribute to the growing field that challenges market efficiency through

possibility of momentum profits (Grinblatt and Han (2005) and Barber *et al.*, (2007)) as well as price implications (Frazzini (2006)).

The final research question is *whether institutional investors engage in herd behavior at market level and whether the behavior is related to specific market conditions*. We draw from an extensive body of literature that investigates institutional herding from Lakonishok, Shleifer and Vishny (1992), Grinblatt, Titman and Wermers (1995), Wermers (1999), Nofsinger and Sias (1999) Sias, Starks and Titman (2001), Gutierrez and Kelley (2007), Puckett and Yan (2008), Yan and Zhang (2009), Choi and Sias (2009), Liao, Huang and Wu (2011), Brown, Wei and Wermers (2014) and Celiker, Chowdhury and Sonaer (2015). However all these studies have examined herd behavior in developed markets. Herd behavior has not been investigated in less developed countries. Thus we investigate this behavior in a small market that is characterised differently from developed markets. Besides testing for existence of herding behavior in the Malawi market, we also test for the behavior controlling for market conditions such as market returns, volatility and market volume.

Herd behavior has implications for stock returns. Dasgupta, Prat and Verardo, (2011b) show that investment managers trade in synchrony with public opinion indicating that they buy stocks when prices are high and sell when stocks are low, which results in return reversals in the long term. A lot of studies have argued that herd behavior is destabilizing and increases volatility as well as contributes to inefficient markets. On the other hand, it has been argued that through its speeding of incorporation of new information into prices, it has a stabilizing effect and contributes to efficient market. We contribute to the existing debate by investigating the existence and effects of institutional herding using trading data in the context of a least developed market. Therefore, price manipulation, disposition effect and institutional herd behavior are three issues that we pursue in this thesis because they have potential to harm price efficiency and economic growth.

We begin our thesis with a detailed literature review in Chapter 2. We present a historical background showing trends from the Efficient Market theory to behavioral Finance. We present detailed theoretical and empirical studies for the concepts that are examined in this thesis, namely *institutional herding, disposition effect and price manipulation*.

In chapter 3, we investigate the misconduct of stockbrokers by analysing profitability differentials between principal brokers and outside investors. We first describe historical episodes of misconduct by market intermediaries and specifically focus on price manipulation

across all financial markets. We explain the motive behind market misconduct. We deploy the methodology of Khwaja and Mian (2005) to analyze misconduct in the Malawian stock market during 11 November 1996 to 18 October 2019. Our findings show that there is no evidence that brokers manipulate prices in the market. Given that theory informs us that brokers use information asymmetry and their position to manipulate stock markets, our results contradict the theory.

In Chapter 4 we investigate whether investors exhibit the tendency to sell winners too early and hold onto losers for too long. We discuss the empirical findings of disposition effect, its sources and how it can be remedied. To test for disposition effect, we deploy the methodology of Odean (1998) which calculates realized gains and realized losses for each investor and then aggregate over all investors and trading days for the entire sample period from 2013 to 2019.

Our primary result shows supporting evidence that investors sell winning stocks more readily than losing stocks. The disposition effect appears to decline over time. We also document findings that a test of rebalancing indicates that there is evidence of disposition effect. However, when partial sales are controlled for rebalancing, the study does not find significant results. We also do not find any evidence that selling decisions are influenced by transaction costs.

In Chapter 5 we examine whether institutional investors herd at market level and whether this behavior is influenced by market conditions such as returns, volatility and volume. We first discuss the relevant literature that explain why institutional investors engage in herd behavior. We test out hypothesis by using portfolio holdings of institutional investors in Malawi from January 2007 to October 2019. We study institutional herding because the trading behavior of institutional investors causes excess volatility, drives prices away from their fundamental values and makes financial systems fragile (Bikhchandani and Sharma, 2000; Filip, Pochea and Pece, 2015). To test for institutional herding, we deploy the methodology of Sias (2004) which directly measures the extent to which institutional investors follow each other over adjacent quarters. The rationale behind our hypothesis is that if institutional herding is revealed at market level, then it would be reflected through differences in the significance of their prevalence across different market conditions. Otherwise, variations in market conditions would not have any impact over the significance of herd behavior.

Our findings show that institutional investors do not engage in herd behavior because the trading information of other institutional investors is not easily available. This means that Malawian institutional investors do not follow the trades of others.

In Chapter 6, we conclude our thesis by summarising the findings and outlining the implications for regulators and the wider economy.

Chapter 2

2.0 Literature review

2.1 Efficient Market Hypothesis

In this section, we briefly discuss assumptions, implications, and stages of efficient markets. Firstly, how theory emerged, then implications, definitions and finally stages of efficient markets.

Fama (1970) suggests that security prices fully reflect all available information, and they change randomly overtime upon arrival of new information. The study argues that asset prices follow a random walk as postulated by Samuelson (1965), which hypothesize that in a competitive market, price changes overtime must perform a random walk with no predictable bias. This implies that there are no patterns that can be exploited, however, if any investor earns excess returns, then they are either due to chance or compensation for the risk level taken. So, one of the key assumptions of efficient markets hypothesis (EMH hereafter) is that asset prices fully reflect all available information, that is security prices reflect the riskiness of an asset indicating that there is a relationship between risk and return. So, given information, security prices should change randomly depending on the news. Put differently, trading decisions are information-based such that price changes should be based on fundamentals of the companies. This means that successive changes in value are independent i.e. a random walk. Malkiel (2003) argues that EMH is premised on the belief that securities markets were extremely efficient in incorporating information about individual stocks and the entire stock market. This cements a view that stock prices would rapidly change as new information arrives and is impounded in the prices. Further, the author states that the EMH is connected with the concept of random walk, a term that characterize a price series where all subsequent prices vary unsystematically from previously prices. This idea is premised on how news is impounded in stock prices that since news is by definition unpredictable then price changes must also be uncertain and unsystematic. This implies that excess return opportunities are unpredictable, where excess return is defined by Ackert and Deaves (2010) as return net of transaction costs and management fees. It also implies that if a market is efficient, then asset prices equal its expected fundamental value [(Shiller 1981)]. Malkiel (2005) posits that if the flow of information is unimpeded and information instantaneously reflected in prices, then tomorrow's price will reflect new information only and will not be correlated to previous price changes.

The implication is that with such full reflection of information, any investor, uninformed or otherwise, will earn a similar rate of return.

In addition, Fama (1970, 1991) suggests a joint hypothesis problem where market efficiency can be tested jointly with a given Capital Asset Pricing Model (CAPM hereafter) of Sharpe (1964), Lintner (1965) and Black (1972). This draws the line between tests of informational efficiency of asset prices and the predicting power of CAPM such that if asset prices do not reflect market fundamentals, then either the market is inefficient, or the pricing model is mis-specified. Thus, Fama (1970) posits that for the hypothesis to hold in a rational paradigm (homogeneity of agents), transaction and information costs should be assumed away. It is important to highlight the concept of rationality with respect to financial markets.

The other key assumption is that investors are rational agents suggesting that investors are relatively homogenous in their expectations with each one of them maximizing their subjective probability and bearing consistent beliefs with respect to the distribution of the factors affecting returns which they update using Bayes¹ rule [(Barberis and Thaler, 2002)]. Thus, Bayesians believe that estimation involves continually updating and sharpening subjective beliefs about the state of the world. It suggests that people update beliefs correctly based on probability distributions. Put differently, market agents see correct signals and that they have consistent beliefs. In addition, agents have superior foresight such that they rarely make mistakes, otherwise their mistakes are not systematic.

Behavioral finance researchers have difficulties with the phenomenon of relative homogeneity. They argue that investors, as human beings, cannot be construed to be consistently rational. Evidence from psychology indicates that while asset prices will change, the updating of beliefs need not take place in a Bayesian fashion. In other words, investors cannot behave the same, as others will react to news more excessively than others. Behavioral finance posits that research findings from cognitive psychology evidence that human behavior is influenced by bias and heuristics and imply a less rational world for investor behavior. This they argue that human behavior can therefore not be construed as homogenous. Furthermore, factors such as levels of education, risk preferences and how information is processed affect how decisions are made. Gavriilidis (2013) posits that while rational paradigm and relative homogeneity point to an anticipated outcome, heterogeneity can give possibility to numerous outcomes either due to

¹ According to economists, rational learning is undertaken in accordance with Bayes rule which is a probability-based rule to infer the outcome of an event given the occurrence of another.

rationality or behaviorism, since bias and heuristics affect how we receive (content) and process (structure) information. Thus, behavioral finance assumes that investors are imperfect in some capacity and so their rationality is bounded.

2.1.1 Stages of EMH

Fama (1970) defines three stages of efficient market hypothesis. The first, weak form hypothesis is where prices fully reflect historical or past information. The hypothesis was that how well are future returns predicted by past returns. This indicates that weak form tests are concerned with the forecasting power of past returns. Following heavy debates on this literature, Fama (1991) recategorize weak form tests to be tests for return predictability covering variables such as dividend yields and interest rates. This follows evidence against the stage of weak form hypothesis. Table 2.1 depicts stages of efficient markets and corresponding information set.

Table 2.1 : Stages of Efficiency Market Hypothesis (EMH) and Information set

Stage	Information set	Role of Analyst
Weak Form Efficiency	Past prices and trading volume	Technical analysis is not meaningful
Semi Strong form Efficiency	Past price and trading volume and publicly available information	Both technical and fundamental analysis is not meaningful
Strong Form Efficiency	Past price and trading volume publicly available information, and private information	Insider information is not advantageous

Source: Tabulated from information drawn from Yalcin, K. C; (2010) Market Rationality: Efficient Market Hypothesis versus Market Anomalies, *European Journal of Economics and Political Studies*, Vol 3(2)

The second, semi-strong form hypothesis is where asset prices fully reflect publicly available information which includes past earnings and earnings forecast, past and most recent released financial statements, everything released appearing in the business press and everything that is considered relevant (Ackert and Deaves, 2010). In view of the fact that most of the tests of semi-strong form relate to tests of adjustments of prices to public announcements, Fama (1991) renames them as ‘event studies’.

The third, strong form is where asset prices reflect both public and private information. Fama (1970) argues that stock markets are efficient processors of information, particularly so if several investors have access to such information, to an extent that disagreements over implications of news do not render the market inefficient. The strong form hypothesis tests whether certain investors had information that was not impounded in prices and so was descriptively called tests for private information (Fama, 1991).

2.1.2 Implications of EMH for Investors, Analysts and Firms

In this section, a discussion of implications of the efficient market theory for investors, analysts and firms is presented.

Finance literature posits that the phenomenon of efficient markets has implications for investors, analysts, and companies. First, for investors, it implies that since prices fully reflect all available information at all times, then investors do not buy overpriced or underpriced securities. They can follow a passive investment strategy because one cannot earn a return more than the market. It should require less effort to track a market. For example, an investor can buy into an index mutual fund or exchange traded index fund. Such investors can buy a diversified portfolio at market prices and attain a generous rate of return like that obtained by market experts or specialists. It also suggests that investors would be compensated depending on risk that they are willing to bear that is, they would earn a higher return if they took on higher risk. It also implies that there would not be any bubbles arising from irrational investors.

The second implication of EMH relates to the role of technical analysts² as well as fundamental analysts³. It suggests that it is pointless to conduct chartism or fundamental analysis to outsmart the market because all the information is already impounded in the security prices and so they cannot successfully generate excess returns. An investor therefore does not require the services of an analyst for advice about trends or whether securities prices are either undervalued or overvalued. Analysts would thus have technically no job.

The third implication relates to companies. Companies release accounting information which communicates financial performance. So, companies should not be worried about accounting choices or rules as they would reflect the reality about prices. More interestingly, companies need not worry about the timing period when there is a need to raise new capital as they can go

² Those who study trends or historical prices in order to predict future prices

³ Those who examine financial statements to ascertain whether stocks are either undervalued or overvalued.

to the market at any point in time to raise money because prices would always reflect the true value. There is thus no need for strategic issuance of securities. Further, it would not matter whether companies choose how to expense items like research and development as the market will read and make sense out of it.

2.1.3 Support for Efficient Market Hypothesis

Numerous theoretical and empirical studies such as Keown and Pinkerton (1981), Dimson and Mussavian (1998), Malkiel (2005) support the axioms that markets are efficient. For example, Keown and Pinkerton (1981) examine the impact of trading on inside information ahead of merger announcements. The study uses the USA Securities and Exchange Commission (SEC hereafter) registered insider trading data from 101 stocks listed on both the New York Stock Exchange (NYSE) and American Stock Exchange (ASE), and 93 stocks from over-the-counter (OTC) market covering announcement dates from 1975 to 1978. They find that investors traded ahead of the announcements as the news about the impending merger announcement was not properly tightly held, largely due to the increasing number of people involved during the negotiations. They also find that market reaction to the news dies down soon after the merger announcement is made. They argue that the evidence suggests support for strong form efficient market hypothesis. One can indeed accept that the evidence that there was no further action after the announcement is in synchrony with what the theory says that an efficient market should have completely reacted just after the event.

There is support for EMH in the twenty first century studies. For example, studies by Malkiel (2005) suggest that even in the top economies like in the USA and Europe, active portfolio managers do not beat the market. Malkiel (2005) study examine results of mutual funds relative to index funds and find continuing evidence that shows underperformance of active portfolio management relative to index fund returns. For example, the Standard & Poor's 500 stock index outperforms mutual funds by a return differential of 2 percent. Although there are few portfolio managers who show superior returns during the selected period, such managers are not able to consistently outperform the market in another comparable period. The author also finds that even at the European level, the Morgan Stanley Capital International (MSCI hereafter) (European) stock index outperforms active fund managers 80 percent of the time over a 10-year period. Further, the MSCI World Equity index outperforms active global funds over a 10-year period ending December 2002. The results suggest that the markets under study do not

avail any arbitrage opportunities that can be exploited by active fund management during the period indicating a reflection of full information. Dimson and Mussavian (1998) carry out a survey of literature and admits that while the concept of efficient market remains elusive, there is more support for market efficiency than challenges against it.

2.1.4 Evidence against market efficiency

While other researchers have found empirical evidence that supports the theory of market efficiency, other researchers do not agree that investors utilize a rational maximizing principle which is central to efficient markets axiom. Proponents of the alternative school of thought believe that stock price determination is also influenced by psychological and behavioral factors of investors (Shiller, Fischer and Friedman, 1984; De Bondt and Thaler, 1985; Black, 1986; De Long, Shleifer, Summers and Waldmann, 1990). Further, stock prices can be predicted based on historical information as well as fundamental valuation metrics (Levis, 1989; Lakonishok, Shleifer and Vishny, 1994). And so literature defines such empirical findings which appear to contradict market efficiency, unless otherwise fully explained as anomalies (Ackert and Deaves, 2010). Frankfurter and McGoun (2001) also define anomalies as empirical findings that vary from theoretical expectations. Their definition does not require an explanation as one can argue that in the context of market efficiency any variation from observed prices constitutes an anomaly. Further, Ball (1978) postulated anomalies as ‘effect’.

Literature posits that there are four main categories of anomalies namely lagged reaction to earnings announcements (also called event studies); the small –firm effect; the value vs growth; and lastly the momentum vs reversal effect. Several such studies include those of Jensen, 1978; Ball, 1978; Watts, 1978; Banz, 1981; Reinganum, 1981; Rendleman, Jones and Latané, 1982; Keim, 1983; Shiller, Fischer and Friedman, 1984; De Bondt and Thaler, 1985; Poterba and Summers, 1988; and Levis (1989). For example, Shiller, Fischer and Friedman (1984) claim that mass psychology is a significant cause of movement of prices of aggregate stock market. The study argues that the efficient market hypothesis ignores the impact of social psychology in the stock price formation process. The evidence from the study of post war events, such as an increase in number of individuals who participated in stock markets; the changes in relationship between investors and market performance; and changes in attitudes demonstrate their effect on valuation of stock prices. They argue that stock market prices were affected by behavioral and social factors other than rationality axioms alone.

In the sections below, we present briefs about each classification of anomalies.

2.1.4.1 Event studies

Literature posits that all firms periodically experience an earnings announcement. For example, in earlier studies that challenged the efficient markets axiom, Ball (1978) reviews literature that investigates market reaction to earnings announcements. The study examines 20 studies from papers covering largely USA (17 studies) and Australia (3 studies). They cover on average 3760 earnings-per-share announcements in the largest of the study for USA market as well as 131 announcements for Australian market.

Ball (1978) observes abnormal returns following earnings announcement and suggests that this is not evidence of market inefficiency but is due to the misspecification of the capital asset pricing model (CAPM hereafter). Although one may argue that the sample periods are in some cases similar while in others overlapping, and so not independent, the survey finds that there are excess returns after earnings announcement, and further excess returns persist over time. In a contrasting study, Watts (1978) interrogated Ball (1978) study and argued that while it was observed that there were abnormal returns after public announcement of quarterly earnings, for a sample of 73 companies listed on NYSE over the period 1950 to 1969, the excess returns were not due to the misspecification of the CAPM, but rather due the market being inefficient especially during the period 1962 to 1965 when after factoring out transaction costs, only brokers would have earned abnormal profits. One can argue that while there are differences in what caused the abnormal profits between the two studies, what is common is that excess returns were observed post announcement of quarterly earnings indicating that the market did not rapidly impound the information.

Jensen (1978) surveys various studies and finds evidence of scientifically and rigorous studies that show support suggesting that markets were not efficient. However, was unable to conclude that markets were inefficient as most of the studies appeared to show some linkages to market efficiency. One could argue that possibly at the time, none had carried out a definitive or comprehensive study to challenge market efficiency theory.

The studies discussed in this section show that events such as announcement of earnings have an effect on stock prices and enable abnormal returns contrary to what the efficient market argues that news is instantaneously incorporated into the prices.

2.1.4.2 Small Firm Effect

A study by Banz (1981) investigates the relationship between market value of the common stocks and stock market returns of the NYSE during the period 1926 and 1975. The study finds that the size of the firm played a significant role in stock market returns over a forty- year period. Specifically, small-sized firms earned higher returns relative to large market valued firms.

Keim (1983) investigates the anomalous negative relation between firm-size as measured by market capitalization⁴ and abnormal risk adjusted returns for a sample of NYSE and AMEX firms over the period from 1963 to 1979. Using data drawn from CRSP⁵ daily stock files for a seventeen year period, Keim (1983) ranks all sample firms based on their market capitalization. The yearly distributions are then divided equally into ten portfolios based on size, in ascending order i.e., from the smallest size market capitalization to the largest firm. The study then carries annual updates of each portfolio as more firms enter or exit the market. Each portfolio contains approximately two hundred firms. It finds evidence that indicates that daily abnormal return distributions in January are different from any other month over the sample period, that is, they had large means relative to other months. Further, the relationship between the size and abnormal returns is negative and more salient in January than any other month over the sample period. Specifically, the study finds that there is a difference in abnormal returns between the smaller firms' portfolio relative to larger firms' portfolios that averages at 8.0 percent over the first 5 trading days in January. This suggests that the returns observed in January observed from small firms challenge the efficient market hypothesis.

Levis (1989) examines the presence of size effect; dividend yields, price–earnings multiple; and share price effects; and their interaction on the London Stock Exchange (LSE). Using a unique set of monthly data return from London Share Price Database (LSPD) for the period April 1961 to March 1985, the study finds evidence that firm size is not only a factor in determining stock price behavior but more interestingly, it also depends on other firm attributes such as dividend yield and earnings yield. This suggests that firm size alone cannot be relied upon as a profitable investment strategy.

⁴ Market capitalization is the product of number of shares of common stock outstanding at the end of the year and the end of year price of the stock

⁵ CRSP stands for Centre for Research in Security Prices of the University of Chicago, USA

The studies discussed in this section show that the size of the firm influences the stock price determination process.

2.1.4.3 Value vs growth

Lakonishok, Shleifer and Vishny (1994) study finds that a wide range of value investment strategies outperformed glamour strategies during the sample period. Specifically, they find that stocks with metrics such as low price to book ratio earned higher returns relative to what was classified as glamour stocks. The authors argue that this was because market participants appeared overconfident in the previous history of the glamour stock and believed that the growth rates of such metrics as earnings, cashflows would continue only to realize that they actually turn out to be lower. The authors argued that such investors have a judgmental error by placing too much weight on past performance to persist. They also find that value strategies are not riskier than glamour stocks and so fundamental risk is not the reason that explains superior returns. The explanation for higher returns varies from the justification of Fama and French (1992) which argued that fundamental risk was the reason for abnormal returns. One can argue that theory posts that higher returns positively relate with high risk, so the argument about fundamental risk being the reason behind super returns has merit.

The empirical study discussed in this section show that financial metrics could be used to predict stock prices.

2.1.4.4 Momentum and reversal

Grinblatt and Titman (1989) define momentum effect as a positive relation between the return of a stock in one period with its lagged return. Such studies suggest that empirical evidence does not conform to rationality axioms and so challenges EMH. Evidence from cognitive psychology indicates that investors do not update beliefs in Bayesian fashion. Recall that Barberis and Thaler (2002) show that the rational paradigm is premised on assumption that investors are relatively homogenous in their expectation, with each one of them maximizing their subjective expected utility and bearing consistent beliefs as to the distribution of factors affecting returns which they update in Bayesian fashion. This is not necessarily the case in reality. Investors may react more excessively to given news that arrives in the market. Studies have shown that investors overweight recent information and underweight less recent data. For example, De Bondt and Thaler (1985) investigate whether investors overreact to unanticipated and instant news events by examining monthly return data from NYSE common stocks for a period covering January 1926 to December 1982. The authors find that when stocks are ranked

on a 3-5 year historical performance, past winners end up as losers while past losers end up as winners, indicating a reversal of returns. This implies predictability, such that one can buy past losers and sell past winners. The key findings show that past losers were up 19.6 percent relative to the market in general, while past winners were down 5 percent relative to the market in general. They find that the effect of overreaction was much larger for losers than it was for winners, indicating that it was asymmetric. They also find that excess returns were earned in January. In addition, the overreaction phenomenon occurred during the second and third year of the sample period i.e., it takes 2 to 3 years to realize a return, but there was no reversal in the first year. The study shows that based on past returns one could earn excess return by buying losers and selling winners which runs against market efficiency.

Jegadeesh and Titman (1993) document evidence that stocks trend. Their study shows that stocks with good (bad) performance during the past year tend to continue to do well (badly) during the next 3-12 months. This implies that investors need time to respond to news. Put differently, information is not reflected immediately into process, but takes some time. Empirical evidence in support of underreaction is documented by Rouwenhorst (1998). The study documents that there is underreaction and later correction of prices which causes positive serial correlation in stock returns.

Poterba and Summers (1988) investigate whether stock prices are mean reverting. Using U.S.A. monthly data and annual returns covering the period 1871 to 1985 of equal weighted and value weighted NYSE returns, they deploy Monte Carlo and variance ratio analytical methods. They find positive autocorrelation in returns over short horizons and negative autocorrelation over long horizons. The results suggest rejection of the random walk hypothesis.

The findings of the studies discussed in this section show that investors are biased, for example, they underweight new information and place too much weight on historical information. They also do not adjust beliefs or new information as predicted by the theory of efficient market hypothesis. There is evidence that shows that others earn excess returns or could have earned excess returns.

2.1.4.5 Summary of evidence against EMH

The foregoing has shown that rational approach postulates that asset returns are a product of risk alone while behavioral approach believes that asset returns are product of both risk and

mis-valuation. Investors are susceptible to biases and deploy heuristics which lead them to making errors in the manner they perceive and process riskiness of an asset.

Anomalies studies suggest that investors can earn excess returns contrary to the axioms of efficient market hypothesis. Developing literature shows that market intermediaries can abdicate their market role in the efficient price determination process and take action that supports the moving away of prices away from fundamental value [(De Long, Shleifer, Summers and Waldmann, 1990)]. In the process, such intermediaries can earn profits more than the investors they intermediate for (Khwaja and Mian, 2005).

Given that studies such as Comerton-Forde and Putniņš (2014) and Siddiqi (2017) show that market intermediaries interfere with market efficiency, and that Mei, Wu and Zhou, (2005) and Khwaja and Mian (2005) show that emerging markets witness manipulative incidents, the question about the role of market intermediaries and how they are governed remains important. The misconduct of some participating market intermediaries to cause harm as shown in Libor studies by Abrantes-Metz, Krasten, Metz and Seow (2012), creates a risk that can affect the integrity of the market generally and specifically for least developed, perhaps more seriously. Consequently, the role of regulation and enforcement in combating behavioral aspects and conduct such as manipulative practices continue to be under the microscope of researchers. In this connection our thesis investigates financial behavioral aspects that challenge efficient markets. We therefore specifically examine misconduct of market intermediaries, disposition effect and institutional herding behavior in a least developed country.

In the next section, we briefly provide an overview of stock market manipulation and discuss empirical evidence.

2.2 Stock market manipulation

From the overarching overview of efficient market hypothesis and its challenges, we now move to review two sources of feedback trading that challenge efficient markets, namely market manipulation and disposition effect. We discuss brief history and provide empirical evidence. We first discuss market manipulation.

2.2.1 Historical Overview

This section reviews definition and types of manipulation in order to provide context to schemes of stock market manipulation. Further, we provide brief real- life examples from the press. The section commences with a brief historical perspective of market manipulation.

The schemes of manipulation date back to as early as seventeenth century when stock markets emerged. Brokers discovered the art of profiting by manipulating stock prices, soon after the founding of Amsterdam Stock Exchange in the early seventeenth century, through bear raids⁶ (Allen and Gale, 1992). They then enhanced the malpractice by combining it with misleading information. Manipulative incidents were prevalent in all stock exchanges that were established around the time until the nineteenth century when it hit the Wall Street with what Allen and Gale (1992) call colourful accounts of manipulation, for example the collapse of a gold corner on Black Friday, September 24, 1869 amongst many other corners.

There was no clear legislation until after the Great Crash of 1929 when the United States (US) securities regulatory authorities responded to public concern by introducing a law, the Securities Exchange Act of 1934 to eliminate manipulation. Literature shows that it was meant to deal with action-based and disclosure-based manipulation. For example, Mei, Wu and Zhou (2005) attest to the fact that these two kinds of manipulation were effectively outlawed. Further, they state that most regulatory bodies across the globe regulate disclosure of information as their main regulatory task.

Since then, there have been continuing episodes of manipulation; for example, several US Securities Exchange Commission (SEC hereafter) action in cases of manipulation as analyzed by Aggarwal and Wu (2006), for the period 1990 to 2001, show incidents like in Wamex Holding Inc⁷, where a firm utilizes nominee accounts to create a misleading peak in volumes through the release of false information and rumours; and also, engaging in prearranged large

⁶ The depressing of stock prices through spreading of false rumours.

⁷ It was a New York based company which traded on OTC Bulletin Board that used false rumours to prop its price.

block of trades that create an impression of information based trade. That the practice prevailed in the twentieth century, even in developed countries despite existing regulation and enforcement suggests that motivation for manipulation remains unclear.

Allen and Gale (1992) study suggests that manipulation occurs in a variety of markets and circumstances by taking on many forms and employing different techniques. The magnitude of its effects can be disastrous including bankruptcy of firms, for example Enron Corp and WorldCom resulting in loss of massive wealth (through savings and jobs) and livelihood.

Manipulation affects both liquid and illiquid markets, emerging or developed markets. For example, Lin (2016) states that the American stock market, the most valuable and respected capital market in the world, experienced a trading session of unprecedented volatility and velocity during the flash crash. In addition, several researchers have investigated the effects of stock price manipulation. For example, Goldstein and Guembel (2008); and Putniņš (2012) document that manipulation distorts prices and harms resource allocation. Other studies such as Aggarwal and Wu (2006) show that it affects prices/returns, liquidity, and volatility. More recently, Imişiker and Taş (2013) and Comerton-Forde and Putniņš (2014) empirical studies suggest that manipulation harms public confidence by distorting fair values through creation of artificial prices and discourages investor participation in markets as it increases trading costs and costs of capital for listed companies. However, literature does not show any consensus over the overall harm caused by manipulation.

Empirically, research is limited by data, for example lack of proper samples of detected and prosecuted cases; and also, the use of noisy empirical proxies for manipulation as suggested Putniņš (2012). Earlier, Cumming, Johan and Li (2011) study suggests that limited research is due to the fact that market manipulation is illegal and so rarely detected and prosecuted.

2.2.2 Definition and types of stock market manipulation

It is interesting to observe that despite a long history of world financial markets dating back to seventeenth century when the first stock exchange was established and manipulative practices first observed, literature does not provide a generally accepted definition of it. While academic studies provide some definitions, the courts interpret certain practices as manipulative schemes and so regulatory authorities define or outlaw the practice differently. The legal definition of manipulation, however, according to Frunza (2015) is an intentional act aimed at misleading investors by controlling or artificially interfering with the market forces of an asset.

Researchers have weighed into the subject, to provide definitions of manipulation. For example, Kyle and Viswanathan (2008) define illegal price manipulation as a trading strategy conditional to undermining economic efficiency both by distorting prices which reflect signals for resource allocation and reducing liquidity. Cumming and Johan (2008) consider manipulation as an array of trading practices that distort prices and enables profiting by exploiting other market participants resulting into information asymmetries. Although there is a variation in the manipulation practices, the authors suggest that there are certain manipulative practices that are construed as standard and so generally understood by the public. For example, ‘front running’ is commonly understood to be the placing of an order by a broker to his benefit, ahead of the client he is intermediating for. Another term ‘insider trading’ is also commonly understood by the public as trading in securities based on privileged information that is not yet made public. In addition, Lin (2016), suggests that corners and squeezes are examples of old techniques of market manipulation and others include wash trading, pumping and dumping (or ramping) and benchmark distortion. Further, Cumming and Johan (2008) however suggest that there are also other manipulative practices that are not well recognized by the public, for example ‘spoofing’ or ‘painting the tape’ where a trader engages in a series of transaction that are displayed to the public to give an impression of activity or price movement like misleading trading. This though is fairly a modern technique and utilizes technology.

Allen and Gale (1992) identifies three different forms of manipulation, namely; information-based, action-based and trade-based manipulation. These are further operationalized by various techniques, a compilation of which is depicted in Table 2.2.

Information based manipulation entails the release of imprecise information or rumours about a firm in order to either inflate or depress its price. For example, there are various techniques that relate to misleading information like ‘bear raids’. A typical real-life example of a bear raid is reported by Sayle (2001) which occurred in 1607, where Isaac Le Maire short the stock of Netherland Dutch East Indies Company⁸ down and covered his position at a discount. Allen and Gorton (1992) state that Harlem Railway⁹ corner was another typical example of a bear raid although it was not successfully covered at a discount.

⁸ Also called Netherlands United East Indies Company (Verenigde Oostindische Compagnie (VOC), established in 1602, was the world’s first multinational, joint stock, limited liability corporation. It was also a government supported trading cartel.

⁹ An American company in which the New York City Council passed an ordinance to allow the company to build a streetcar street. The price of the company rose from \$9 to \$75 and the members of the council conspired to sell the stock short and force the price down. A large shareholder, Commodore Vanderbilt heard about the plot and secretly bought out entire stock of the company. He later cornered and forced the council to cover their position at \$179 per share.

Table 2.2: A glossary of techniques used to describe manipulative activities in different financial markets.

Technique	Description
Bear raiding	This is a heavy or concerted selling or short selling in order to depress the price of a security. Typically, brokers spread unfavorable rumors about a company to depress its stock price
Cornering	Acquiring a large position in a security to gain control of the supply of the security to increase its price. Applies to spot and futures markets
Pump and dump	Traders who are long in a security, spread rumors or false information about it to pump the price up, until a target price is reached, the trader then dumps the security, and often the price falls. If the dissemination of false information or rumors through the media, internet or other means to inflate the asset price, it is called 'hype and dump'. If it is meant to depress the price, then it is called 'slump and dump'
Wash trading/Sales	Selling and repurchasing the same security to generate activity and increase the price but without really changing the ultimate real beneficiary of the stock
Front running	A trader executes his order, ahead of large price moving order in order to profit from the large order
Painting the tape/screen	Traders create trading activity and spread rumors to raise the price of a security or benchmark-common in high frequency trading
Quote matching	A trader has foreknowledge of a large trader's future order and places an exact order ahead of it, to his advantage
Short squeezing	A trader takes a big position in spot market to fix a group of short sellers out of their position OR a trader takes a controlling position in the supply of an asset then exploit other participants that need the underlying asset to close out short position
Spoofing	A trader makes a series of buy orders or sell orders and immediately cancels them to discern the intentions of other market participants
Boiler room	A group of salespersons contact a potential client and persuade them with pressure sales tactics to pursue an investment
Pegging and Capping	Placing orders to effectively prevent the price from moving up or down in respect of stock markets or Practice of an investor buying large amounts of an underlying security close to the expiry date of the derivative held by the investor.
Pools	Pools are when a group of manipulators trade shares back and forth among themselves to influence prices and create the appearance of trading volume
Matched orders	Matched orders are pairs of buy and sell orders placed by different but colluding parties at the same time for the same price and volume
Churning	The excessive trading by a broker to generate commissions rather than profits for the client. It is also called overtrading.

Source: Compiled from Scott (2003) Putniņš (2012) Frunza (2015) and Lin (2016)

Historically, newspapers and boiler rooms have been a predominant mechanism used to spread false information. Due to technology, there has been a transformation where internet has been utilized and more recently social media platforms such as Facebook, Twitter (now X) are used to disseminate information more quickly and widely. Lin (2016) suggests that cybernetic market manipulation is an emerging technique of market manipulation arising from financial technology that is very disruptive and consequently calls for new ways of market regulation and understanding manipulation in order to protect investors and markets.

Allen and Gale (1992) state that action-based manipulation entails taking a course of action that affects the value or perceived value of the firm. For example, a director may paralyze certain operations like a product line shut down to influence a price fall. Other techniques include corners or squeezes. Another example, Eichenwald (1989) reports about the Hunt brothers who manipulated the Silver market prices by simultaneously purchasing silver futures contracts and millions of ounces of silver. In 2008, Porsche¹⁰ acquired shares in Volkswagen (VW hereafter) but did not disclose its ownership and eventually cornered the market in VW shares, leading to huge losses by hedge fund managers who had shorted VW stock only to see the stock rise in price and cover their positions at a high price. Only 5 percent of VW shares were available for trading (BBC News Online, 2008). There is however very little literature on action-based manipulation since manipulator rides on signalling with false information, and so research around information-based manipulation is suggestive of action-based manipulation.

Allen and Gale (1992) posits that trade-based manipulation takes place when there are attempts to manipulate security simply by buying and then selling, without taking any publicly observable action to influence the value of the firm or releasing misleading information to distort the price. Put differently, it entails influencing the price of a security through trading. The techniques include pump and dump strategy; front running, wash sales, and more recently painting the tape/spoofing. For example, in a pump and dump manipulative scheme, a manipulative entity takes a position in a stock, then fraudulently promotes the stock to artificially increase the price before selling it to unsuspecting investors. The price often falls after the sale. Lin (2016) reports that this technique has existed for centuries, for instance, the South Sea Bubble in the 1720. It was also common in the USA for penny stocks during the

¹⁰ Porsche, a motor trading company, did not declare its shareholding control in VW shares and so, traders unknowingly shorted the stock by borrowing from Porsche, selling them to Porsche, buying them back when the price rose from Porsche and returning them to Porsche.

1990s and dot.com bubble period, where the scheme involved the use of boiler rooms to aggressively promote the stocks to naïve investors. In past few decades, boiler rooms, internet chat rooms, websites and spam emails have been used to perpetrate pump and dump schemes. More recently, social media (such as Facebook and X, formerly Twitter), is a medium through which the scheme is carried out amongst others.

Wilchins and Brettel (2010) and Murphy (2010) report Goldman Sachs Group Abacus 2007-AC1 deal in synthetic collateral debt obligation in which an informed trader, a hedge fund manager named John Paulson got into a deal and bet against risky subprime mortgages (home loans repackaged into bonds) using derivatives. Goldman Sachs was aware that European banks such as IKB Deutsche (IKB hereafter) and ABN Amro (herein as information seekers) wanted to take a risk from such subprime mortgage bonds if they were selected by an independent manager. So, Goldman identified ACA Management LLC to work with Paulson to identify a portfolio of securities to be purchased by its clients but did not disclose the information that Paulson wanted to short the securities. Goldman eventually put up a deal which IKB (\$150m) and ABN (\$909m) bought into. In the midst of the crisis, the bonds defaulted, and Paulson was paid from the investor losses in the amount of about \$1billion (IKB and ABN Amro). While IKB lost all its moneys, ABN which suffered worst was later acquired by a consortium of banks. This is an empirical example of theory suggested by Aggarwal and Wu (2006) of three investor model, in which a manipulator (Goldman Sachs) profit and manipulates information seekers. The manipulator contributed to the financial crisis by magnifying the losses in the housing sector.

More recently, high frequency trading has been associated with manipulative incidents. For example, the Flash crash of 6 May 2010 was reported to be caused by ‘spoofing’ or painting the tape. Kirilenko, Kyle, Samadi and Tuzun (2017) empirically analyzed the events in the lead up to the May 2010 flash crash. The authors argue that it was not caused by high frequency traders but rather the compelling demand to act swiftly failing which price changes adversely affect slow traders and traditional market makers. However, five years later, in a twist of events, Viswanatha (2016) and Whipp and Scannell (2016) report that Navinder Sarao, a British trader pleaded guilty to charges levelled against him for partly causing the Flash crash through spoofing, suggesting that high frequent traders were behind the flash crash that initially affected the derivatives market and eventually affected the stock market. Sarao flooded the market with fake orders and made \$40m in illegal profits.

There are suggestions that high frequency trading firms are able to manipulate the market by submitting and cancelling orders to discern the intentions of the market participants within a short period of time. Lin (2016) suggests three reasons. First, due to their superior technical abilities, they gain access to exchanges and dark pools, and special access through high-speed cables and order feeds. This enables them to see order flows coming into the exchange or dark pool, and so can execute trades faster than others to their advantage. Second, they can manipulate the marketplace by submitting and cancelling orders to discern intentions of other participants. That is, they can do spoofing. Last, they can manipulate prices by routing and rerouting customer orders to forums that are more advantageous to the firms relative to their customers. More importantly, Lin (2016) suggests that high frequency firms have informational advantage through special access to servers, high speed cable lines and customer orders which enables them to execute orders ahead of others to the disadvantage and the detriment of others.

Murphy (2018) reports that at the peak of crypto assets, anecdotal evidence suggests that pump and dump schemes hit the crypto market where speculators piled into one cryptocurrency at one time and inflated its price, invited others to invest in it, drove the price further up and those who pumped the price up cashed out rapidly. The author also reports that being a loosely regulated market, it was marked by false rumours and marketing guarantees.

2.2.2.1 Real life examples from the Press

In this section, examples reported in the press relating to the pink sheets¹¹ and rate fixing popularly known as Libor scandal are discussed. These include cases where individuals, investment firms and banks have been fined or individuals have been jailed for manipulating asset prices or benchmarks.

2.2.2.1.1 Examples from the Pink Sheets

One illustration of how the stock market was manipulated, particularly through pink sheets in the USA is written in a book titled '*Born to Steal*', by Garry Weiss. Weiss (2003) documents how illegal stock market manipulation scheme prevailed on the Wall Street in the early 1990's and dot.com period from 1992 to 1999. The villain in the book is Louis Pasciuto, a young man, who deployed high pressures sales tactics and aggressively promoted worthless stocks

¹¹ A quotation system established by National Quotation Bureau for stocks and bonds in the paper-based stocks, pink sheets or if they were bonds, yellow sheets.

including outright deceit to naïve investors at inflated prices. The author states that ex-convicts and persons involved in organized crime operated and owned brokerage houses which had branches while others operated chop houses. They infiltrated and established a network of stock promoters, securities dealers and boiler rooms to engage in pump and dump manipulative scheme. Chop houses were middlemen between a stockbroker and a company raising money i.e. their role was to promote stocks that traded over-the-counter (OTC). They focused on microcap securities market i.e. stocks that trade on the OTC Bulletin Board or pink sheets. They had control over nominee accounts. They acquired a large block of securities at a negotiated price, often below the quoted offer/ask spread and sold the stock to brokerage customers at the quoted offer/ask price to unsuspecting or gullible clients. They kept prices of stock up by constantly engaging in cold calling clients to buy stocks all the time. Traders such as Pasciuto, guaranteed the money through selling warrants¹². They misrepresented the warrants as pieces of paper that would definitely increase in price. They also promoted companies that were not operating i.e. not generating any revenue.

Weiss (2003) states that chop houses targeted unsophisticated people from rural areas and towns such as Utah and Nebraska; retired and naïve farmers, and old people, convinced them to send smaller amounts of money to buy stock that did not actually exist. In some cases, they targeted profit chasing millionaires in the states like California. It was pure securities fraud. They abused investors trust and exploited investor psychology.

Weiss (2003) posits that chop houses held themselves as registered stockbrokers when they were not. They misrepresented themselves in a big way. As stock promoters, they were expected to be linked to an investment banker/broker, an arrangement where they would get part of a commission earned by a broker. In reality, they did illegitimate business. They pretended to sell stocks and pocketed the funds. The author reports that chop houses committed thievery in the amount of \$10 billion in early 1990s. They just committed securities fraud. For example, they pushed the stocks onto the public at inflated prices and sold stocks that never was. They committed other scams such as insider trading and junk bond scandals. Furthermore, they guaranteed profits, sold unsuitable securities to investors. Weiss (2003) documents that chop houses recruited less formally educated street kids or college drop-outs without knowledge about investments. Since chop houses were themselves fraudulent scams, bent at ripping investors off by selling non-existent stocks, the staff were taught sales pitching skills.

¹² Warrants were a wager on the future price of a stock and works the same way a stock option, by giving an investor a right to get a stock at a certain price sometime in the future.

They sold a story rather than a business. Chop houses were not subjected to regulatory oversight and so other traders did not possess a trading licence, series 7 which was authorized by National Association of Securities Dealers (NASD) now Financial Industry Regulatory Authority (FINRA), although they held themselves out to clients. The chop houses did not have adequate procedures to prevent misconduct in connection with execution of orders.

Weiss (2003) reports that sadly, regulatory authorities paid little attention to the on-goings of the penny stocks sector despite receiving complaints, and disregarded observations from even one of their own staff early on. One would argue that regulators did not understand the business that chop houses were in or where the risks lied, perhaps because it is small relative to large-capitalized securities market. There was cursory attention given to their books; and to complaints lodged against them. Despite client statements depicting aggressive sales practice, regulators did not pick them up. They focused their examination on ordinary commissions yet chop houses had excessive mark ups that were classified as trading profits, termed 'rip' which was built into the prevailing market price of a stock. The regulator may have missed the red flags, from unauthorized persons, high staff turnover, complaints to examination of books and governance. One company, led by Pasciuto himself, had one employee, being the CEO and an employee.

Another example is where Henriques (2003) reports about Hartley Bernstein, a young lawyer who in his early career rigged thinly traded stocks and defended top three penny stock manipulators at the time, and was later found guilty of securities fraud in 1999, and eventually forfeited \$850 000.00 in illegal profits. While waiting for sentencing, he established a website styled Stockpatrol.com that warned investors about scams. Bernstein helped regulators to go after manipulators, because he knew them, and so testified against them. Due to this, the judge sentenced him to two years' probation.

There are several other examples where the regulator, Securities and Exchange Commission (SEC hereafter), pursued manipulators and levied fines. For example, SEC (2009) reports charging 8 participants in a penny stock manipulation scam that inflated market prices of four stocks. The manipulators raked in \$6.2 million in profits after dumping the shares. The perpetrators operated a website and sent out misleading press releases of the companies to hype the stock. In this particular example, they misled investors on September 1, 2006, that the profits for July 2006 would be 7.5 times more than that recorded for July 2005. The misleading press releases created an impression of real demand for stocks. They also pumped up the market

price using wash sales, matched orders, and other techniques by artificially inflating the market price.

More recently, there have been cases where ownership of promoted stock is hidden and presented by promoters as neutral parties. For example, SEC (2014) report charges three penny stock promoters who coordinated by taking a large control of stake in microcap companies and hyped up the price through newsletters to potential investors. The price fell after marketing efforts stopped. The SEC argues that the perpetrators created demand and increased the price of the stock. In addition, the SEC (2018) reports that Morrie Tobin and three others were charged for illegal sale of stock of 2 public companies. The SEC argued that Tobin hid ownership and control over the companies using offshore entities to hold his stock and established accounts to sell the stock to Swiss based company operated by British citizen. Tobin also paid a promoter to hype the stock creating an impression that the recommendation was from a neutral third party. The price moved from \$1.05 to \$2.21 per share.

These examples illustrate how market intermediaries manipulate penny stocks through pumping and dumping, misleading information, corruption, and outright fraud.

2.2.2.1.2 LIBOR Scandal

A case in point is where banks such as Barclays, Citigroup, Deutsche Bank, JP Morgan Chase, Royal Bank of Scotland, and Union Bank of Switzerland (UBS hereafter) were reportedly fined by regulatory authorities during the period 2012 to 2015 for colluding to manipulate interest rates. For example, Vaugh and Finch (2017) report how traders rigged rates to avoid losses through loan payments and being perceived as lacking cash, by manipulating the London Interbank Offer rate¹³ (Libor), popularly known as the Libor Scandal. Its derivation was largely by opinion of brokers through electronic submission of what they perceived as estimates of their borrowing costs. It thus relied on the honesty of the brokers and yet they had a direct interest in the ultimate average set rate. It later turned out that banks submitted rates that were not a reflection of their borrowing cost but distorted rates that would fit within the middle pack of the selection criteria, to avoid being perceived as high risk.

¹³ It is a basic rate of interest used in lending between banks on the London interbank market and also used as a reference for setting the interest rate on other loans.

Vaugh and Finch (2017) report that an employee of a Swiss Bank UBS, Tom Hayes, based in Japan, influenced brokers based in London, who were making Libor submissions by offering them payments for cooperation through emails. He colluded with several others to rig the rate in their favour. Technically, traders generate income from 'spreads', the difference between ask and bid price, however Hayes made money from relative value trading i.e. he searched for patterns, price anomalies and exploited them. For example, if two assets were trading at different prices, he would buy one and short the other, betting that the spread between the two would narrow down. The authors report that due to credit crunch and fall of banks such as Lehman Brothers and Bear Stearns, lending amongst banks themselves without collateral changed and so the interest rates on long-term loans increased. Libor also increased and there was no trading for cash for over 30 days. The increase in Libor meant that those who owed others had to pay more in interest, and that hit their bottom lines. There were questions raised as to whether the increase in Libor reflected the credit squeeze. This motivated investigations. Vaugh and Finch (2017) report that there were suggestions that banks were submitting intentionally low estimates of their borrowing costs to avoid being perceived by other banks as being desperate for cash and so others were suspicious that the Libor was being distorted and, in the process, affecting large sums of money around the world. UBS eventually settled \$1.5 billion for wire fraud committed at the Japanese office.

BBC News (2013) report that Barclays also played a part in fixing Libor submissions in order to give a healthy picture of the banks' credit quality and its ability to raise funds. Higher rate submissions give a picture that it is desperate for cash from the market. Rose and Sessia (2013) confirm that Barclays admitted having manipulated the Libor submission after its CEO Robert Diamond resigned, blaming a few employees for reprehensible action. Barclays was fined \$450 million by both UK and USA regulators.

The examples given above indicate the distortion of the Libor where banks were avoiding to pay large interest and derivatives payments that reflected true rising interest rates and the realistic economic environment at the time to their advantage. The distortion of the rate, as a benchmark, indirectly influences all other financial contracts that utilize it as a valuation metric. It also shows that the collusion was systematic indicative of global actors operating in concert.

2.2.2.1.3 Front Running

This occurs when market intermediaries execute orders unfairly. For example, SEC (2013), the US securities regulator charged a Dallas-based trader for executing large block trades for firms' clients that had great potential to increase the price. The trader profited by over half a million dollars by routinely purchasing securities in his wife's accounts ahead of clients. Guthrie (2015) documents a case where the UK FCA secured a 19-month jail term for a trader, at a hedge fund for front running. The author reports that the trader maintained two column order-book, one for big stock purchases requested by clients while another was for smaller order the broker placed first on his own behalf in anticipation of price increases. The investigation covered a period from 2010 to 2014 indicating the complexity and intricacies required to prove the case due to modern schemes. Binham (2019) documents a case where a former top employee of HSBC bank, named Mark Johnson, former Chief Currency dealer was found guilty of front running by tipping off colleagues who traded for the bank itself ahead of processing its client order, Cairn Energy group. The bank was expected to convert proceeds of an asset sale from dollars to sterling in a deal amounting to \$3.5 billion in 2011, and it traded ahead of its client.

2.2.2.1.4 Churning

The term refers to the practice of excessive trading in the clients account with the purpose of generating more commissions. The main source of income for brokers is commissions. It comes from the buying and selling of securities. Put differently, it comes from moving money. So, other than a portfolio appreciation, brokers earnings are related to volume of transaction in clients' accounts. Metz (1971) writes that brokers have a conflict of interest between managing clients' investment needs and brokers income. So, given this, there is pressure to generate more commissions and open more accounts. The author suggests that broker recommendations may be motivated by the need to generate more commissions.

Guild (1992) reports that although the practice of excessive trading is common amongst stockbrokers, mutual funds also churned with clients' accounts in the 1990s. The author states that investors were awarded amounts ranging from \$100 000 to \$1.5 million for complaining against churning and that most mutual funds required complainants to sign confidentiality agreements as conditions of settlement. More recently, Welch (2009) and FINRA (2009) report that a brokerage styled Robert W. Baird & Company was fined \$0.5 million for reverse churning i.e. where clients' accounts were charged when they had not recorded any activity.

2.2.2.1.5 Summary of Real-Life Examples

The above real-life examples show that manipulative acts are executed in various types of markets such as the stock market, foreign exchange, derivatives market, and crypto-asset markets to mention just a few, using several techniques. Compared to use of newsletters in the past, the current medium of modern transmission is largely driven by technologies, for instance, high frequency trading, social media, and internet. It is orchestrated by market intermediaries, licensed or unlicensed traders, through various mechanism like trade activity. In some cases, it can disrupt an entire market like a Flash crash. Manipulative acts betray the trust of investors, and market participants; and affects the integrity of the market. Manipulative acts are motivated by idea of gaining profits or limiting losses in derivatives markets as registered in Libor scandal. Most importantly, the examples show that manipulative schemes disrupt and distort the asset price discovery process with deceitful and misleading information. This suggest that the prices that may be reflected on the market may have been inefficiently derived. Others argue that there is complicity by regulators in allowing a seemingly perceived inefficient financial system. Sadly, although regulatory authorities have penalized the perpetrators, the acts continue to go on and in new techniques such as spoofing. Investors continue to be defrauded, perpetrators in some cases disguise illicit proceeds, and eventually prices are manipulated. It appears that the old techniques are being played on new media platform.

2.2.3 Empirical Evidence

In this section, we discuss theories of manipulation and empirical studies. We start with theoretical studies that underpin these empirical studies.

2.2.3.1 Theoretical Studies

There is a lot of theoretical literature that presents economic models that depict insights into conditions under which manipulation may be possible and enable excess returns. For example, Allen and Gale (1992) show that price manipulation is possible regardless of price momentum and market corner, assuming incomplete information. They theorize that as long as information is asymmetric, investors become uncertain about the intentions of a large trader and so engage in a pooling which allows manipulation to be profitable.

Mei, Wu and Zhou (2005) present a three-trader and two asset model in which they argue that smart money investors manipulate the price process by exploiting investors' behavioral biases to make a profit. They test the model empirically by utilizing data from the USA covering January 1980 to December 2002. They show that smart money investors can generate profits through strategic trading. They present evidence from prosecuted pump and dump cases of manipulation from the OTC bulletin board and pink sheets. The study demonstrates presence of increased volatility, voluminous trading and momentum trading which is consistent with their model. The model also shows how smart money creates an environment that allows an irrational investor to make mistakes which are eventually exploited by the former. While the model resembles that of De Long, Shleifer, Summers and Waldmann (1990) and also some aspects of Aggarwal and Wu (2006), the key difference is that in Mei *et al.* (2005) study, the rational speculator initiates the manipulative trend and is not affected by limit to arbitrage while the De Long *et al.* (1990) study, the manipulator rides the trend created by good news instead of correcting the mispricing and his action is affected by limits to arbitrage. What is however common and clear is that strategic trading by smart money investors distorts price setting processing by moving asset prices away from fundamentals which works against making the markets efficient.

Siddiqi (2017) models price manipulation in a microstructure context with three investors, namely individual, institutional and the broker. The author posits that a broker can manipulate prices by sending misleading signals through research report, while maintaining credibility if institutional investors do not possess superior information. This is likely obtainable where competition is lacking. The author posits that stock manipulation is a difficult problem in less developed countries or emerging markets.

2.2.3.2 Empirical studies

In this section, empirical studies that document evidence from trade-based manipulation are discussed.

Khwaja and Mian (2005) investigate unchecked stock price manipulation in Pakistan, by examining trading patterns of principal brokers comprising 2.2 million transactions during the period December 1998 to August 2001. The study finds that brokers engage in collusive behavior and earn between 50 to 90 percent higher returns off outside investors. The authors posit that manipulative rents account for about 44 percent of total earnings by brokers. Further,

by testing for pump and dump manipulative scheme, they find that principal brokers affect future returns. There is limitation of data in the study by Khwaja and Mian (2005). Firstly, trades are aggregated at broker level for given stock. Secondly, there is lack of information at investor level such that they do not know who is an intermediary or a principal broker. Lastly, there is no data for unfulfilled trades. This renders their assertions very pessimistic of exploitative broker behavior. For example, Imişiker, Özcan and Taş (2015) and Aaron, Koesrindartoto and Takashima (2018) argue that data aggregation by study of Khwaja and Mian (2005) impose a bias on their broker return computation because of proxy usage of average price. Further, they posit that the measure of annualized nominal rate of return (ARR) does not fulfil linearity assumptions although it meets other tests of free cardinality and ordinality measurement.

Khwaja and Mian (2005) suggest that price manipulation stems from principal trading while De Long *et al.*, (1990) posit that trend chasing is a source of manipulation. While Aggarwal and Wu (2006) posit that successful manipulative strategy requires collusion amongst players, Khwaja and Mian (2005) study finds that information asymmetry allows a single broker to artificially move prices and make money off other investors which is consistent with theory by Mei, Wu and Zhou (2005). While the study by Khwaja and Mian (2005) suggests that behavior by brokers explains why there is underdevelopment of equity markets in emerging countries, one would claim that this case may prevail in least development countries as well.

Aggarwal and Wu (2006) examine manipulators' trades in the USA, in the presence of information seekers with the objective of investigating stock market manipulation and its impact on efficiency. The authors posit that a higher number of information seekers signals demand for existing stocks which improves market efficiency but also avails an opportunity for manipulators to enter the market. By examining price and volume effects from 145 prosecuted cases during 1990 to 2001, and conducting a cross-section regression analysis, they find that stock market manipulators drive away information seekers/arbitrageurs. These informational seekers promote competition over price. The manipulators' actions make the market less efficient. Further, the authors find that since information seekers realize that they are being manipulated and are not making any profits, they thus exit the market. Aggarwal and Wu (2006) finds that about 48 percent of all trades that are manipulated, occur at the OTC Bulletin Board and the Pink sheets. Further, the authors find that 64 percent of sampled cases are manipulated by brokers, followed by large shareholders who manipulate 31.7 percent of the cases. They also find that manipulated stocks are characterized by high volatility, high

returns and increasing liquidity during the manipulation period. The study argues for the need of government regulation to improve efficiency and restore effectiveness of arbitrage. The implication of the study is that manipulators negatively affect market efficiency.

Azad, Azmat, Fang and Edirisuriya (2014) examine the relationship between unchecked manipulation, excessive trading and weak form inefficiency in Bangladesh, India and Pakistan. The study extracts evidence from legal cases and analyze price-volume relationships using daily stock prices and volume for the period 1990 to 2010. Using various econometric methods, the authors document empirical evidence of weak-form inefficiency and so claim that such markets are a fertile ground for manipulation. The study finds widespread evidence of manipulation that comes from excessive trading which creates artificial price and volume movements, consistent with findings of Khwaja and Mian (2005). However, unlike the study of Khwaja and Mian (2005) which utilizes trading records, Azad, *et al.*, (2014) utilize legal cases to examine price-volume relationships. Specifically, they focus on large index movements and not stock level price movement.

Imişiker *et al.*, (2015) investigate unusual trading behavior in Turkey (Istanbul Stock Exchange) by examining brokerage trading records during the period 2003 to 2006. The study analyzes intraday trades, covering 104.5 million transactions, from 1172 brokers, and 269 stocks. The authors' findings suggest a positive correlation between proportion of manipulative trades and return of a broker. Specifically, they find that 76 percent of all trades are consistent with pump and dump manipulative scheme compared to 58.3 percent on Khwaja and Mian (2005) study. They posit that this proportion is not wholly attributable to manipulation as it may also be influenced by stock liquidity and turnover which are consistent with the pump and dump scheme. However, they find that unlike Khwaja and Mian (2005) study, where brokers earn between 50 to 90 percent higher returns than outside investors, the manipulating brokers do not earn significantly high returns in Turkey (2 to 4.5 percent), indicating that it might be challenging to engage in pump and dump scheme in a fairly developed country than in an emerging country. Aaron, Koesrindartoto and Takashima (2018) confirms similar results for Indonesia capital market. Both Imişiker, Özcan and Taş (2015) and Khwaja and Mian (2005) compute brokers' profit using annualized nominal rate of return (ARR hereafter). However, Imişiker, Özcan and Taş (2015) modify the methodology by using actual price instead of average price to compute profits. The methodology is therefore termed annualized unbiased rate of return (AURR hereafter). It enables them to exactly compute profits earned from intraday trades.

Aaron *et al.*, (2018) analyze trading patterns by stockbrokers in Indonesia capital market during the period January 2003 to December 2004, and document evidence of manipulative practices. The study covers 13.3 million transactions, 174 brokers and 345 stocks. The study finds that principal brokers manipulate about 60 percent of all trades conducted. In addition, principal brokers earn between 59-92 percent higher annual returns than intermediary brokers. Further, their trading profitability depends on level of principalness and on investment strategies. Stockbrokers who have high trade imbalances are manipulated by those with low trade imbalance. The authors explain that those with high trade imbalance engage in herd behavior because they have diversified trading strategy while those with low trade imbalance have concentrated trading strategies. Unlike in Khwaja and Mian (2005) study, they find that small caps and low liquid stocks are less targeted for manipulation, instead it is high capitalized and highly liquid stocks that are manipulated. The study measures trading profitability using both methods of ARR and AURR of Khwaja and Mian (2005) and Imişiker, Özcan and Taş (2015) respectively. Due to lack of availability of individual data at investor level like in Khwaja and Mian (2005), they use a measure of principalness, to determine between principal and intermediary trades. One would argue that there were two stock exchanges (a private, Surabaya Stock Exchange and public, Jarkata Stock Exchange) during the sample period, prior to the merger in 2007 such that it is not clear which between them covered a larger market size. Secondly, given an old history of the exchange, dating 300 years ago, and its recent reforms history since 1977 relating to deregulation in banking and capital markets, a sample of 2 years may not be representative of the scale of misconduct in the Indonesia capital market. It may suggest specificity to a particular period of transformation.

Neupane *et al.*, (2017) examines concluded prosecuted initial public offerings (IPOs) in Indian market. The study covers a period between 2006 to 2011, with a sample of 228 IPOs. They find that a syndicate of intermediaries obtain positive returns in manipulated IPOs during the first day of listing i.e. median return is 27 percent for first day (7 percent weekly) compared to 4 percent (7 percent weekly) for non - manipulated IPOs. They also find significant proportion of bulk trades that come from a syndicate of brokers who manipulate the market. Further, the authors find that there is significant high trading turnover (approximately 7 times) in manipulated IPOs on the first day than in non-manipulated IPOs. This suggests that manipulated stocks are linked to significant high volume of bulk trades. The manipulation dented the IPO activity and confidence of investors. Neupane *et al.*, (2017) posits that information asymmetry offered the brokers an opportunity to attract information seekers and

harm market efficiency. The brokers operate in a syndicate consistent with findings of Aggarwal and Wu (2006) and Khwaja and Mian (2005) to engage in pump and dump manipulation scheme by artificially moving the security price up with large trades. While they use a unique approach as a tool to determine prevalence of manipulation, however, it identifies cases that were overlooked by regulators. This calls for vigilance for regulatory action.

There are several other empirical studies that document evidence of manipulation. For example, İmişiker and Taş (2013) investigate specific firm characteristics that determine probability of individual stock being manipulated in Turkish market. They find that smaller free float and small capitalized firms are highly susceptible to manipulation. In addition, stocks that have a history of being manipulated combined with high leverage ratio are highly likely to be manipulated. Comerton-Forde and Putniņš (2014) estimate the frequency and investigate the economic underpinning of closing price manipulation in Canada¹⁴ and USA stock markets for the period January 1997 to January 2009. They find that about 1 percent of closing prices are manipulated, out of which a minute proportion is successfully detected and prosecuted. Further, they find that stocks with high levels of information asymmetry and medium to low liquid stocks are susceptible to manipulation. In addition, stocks with high levels of mutual fund ownership are manipulated towards end reporting period.

Huang and Cheng (2015) investigate effects of pump and dump manipulation schemes and stabilization on stock prices in Taiwan during the period 1991 to 2010. Using a data set of 118 prosecuted cases, they find that consistent with dump and pump schemes, there is high volatility in stock returns. For example, they find that average cumulative abnormal returns (ACAR) is approximately 30 percent, while Khwaja and Mian (2005) find a range of 50 to 90 percent. This suggests that manipulative schemes have a negative effect on price efficiency.

2.2.3.2.1 Empirical evidence from manipulated benchmarks: Libor

Gandhi, Golez, Jackwerth and Plazzi (2019) investigate libor submissions by banks during the period 1999 to 2012. They document evidence consistent with libor manipulation which was geared to profit manipulator from banks' holdings of libor related products. The study shows that libor manipulation was prevalent for banks incorporated outside the USA suggesting that weaker enforcement allowed manipulation of the benchmark. For example, banks outside the UK misreported their submission to generate profits from products linked to libor. Fouquau and Spieser (2015) empirically investigate libor malfunctioning during the period 2005 to 2012.

¹⁴ Toronto Stock Exchange and TSX Venture Exchange and for USA-NYSE and AMEX

Using statistical methods, they find irregular libor patterns and significant structural breaks that suggest possible manipulation. For example, they single out specific dates of 9th and 10th October 2008 when Libor was unstable. In addition, they find that banks operated as a cartel in libor submission consistent with findings of Aggarwal and Wu (2006) that manipulators operate jointly. Abrantes-Metz *et al.*, (2012) investigate whether banks engaged in anticompetitive behavior. By examining specifically one-month libor submissions for a period January 2007 to May 2008, they find anomalies within individual quotes, but did not find evidence consistent with effective manipulation.

These studies document presence of collusion among manipulators and demonstration of non-competitive behavior.

2.2.3.2.2 Empirical evidence from other financial markets

2.2.3.2.2.1 Futures markets

Ni, Pearson and Potesman (2005) investigate options trading on the stock price dynamics around option expiration dates and profitability of proprietary traders. They examine USA data from 1996 to 2002 for 2500 optionable stocks listed on various exchanges. The study shows that stocks with listed options cluster at option strike prices on expiration dates compared to those without options. The study explains that hedge rebalancing and price alterations are responsible for clustering. They show that returns are distorted on average by 16.5 basis points translating into movement of market capitalization of optionable stock by US\$9.1 billion per expiration date. The high probability of stock prices closing near options prices is motivated by the options written on them. They also find that proprietary traders who write options in the week leading to expiration of the options earn approximately 2.6 times higher premia than they would pay out on expiration data. In addition, they earn profits consistently. For example, out of 72 expiration weeks, premia exceed payout in 93 percent of the time. The authors however caution that hedge rebalancing and manipulation are not the critical factors leading to clustering.

Atanasov, Davies and Merrick (2015) examine financial intermediaries' role in manipulating orders in platinum and palladium futures contracts. They utilize publicly available court records and daily settlement prices of futures contracts traded on the New York Mercantile Exchange during the period November 2007 and May 2008. They find that hedge fund manager placed unusually large orders at the closing period to influence the contract settlement price to benefit

his compensation. Specifically, they find that floor traders did not correct the uncompetitive high closing prices but rather executed the unusually large orders. The failure to correct distorted prices is consistent with study by DeLong *et al.*, (1990). The authors explain that tacit collusive behavior was apparent amongst the traders, consistent with the findings of Aggarwal and Wu (2006) and Khwaja and Mian (2005) who observe collusion in pursuit of common economic interest.

2.2.3.2.2.2 Foreign Exchange Markets

Vitale (2000) develops a two-auction model to investigate how irrational traders can profit from informational advantage through random orders in a foreign exchange market. The author shows that irrational traders can distort the learning process of a dealer to impede distinction of uninformed orders from informed one by incorporating noise in the order flow. This enables the dealer to provide liquidity at a cost which is eventually exploited by irrational traders. Vitale (2000) claims that since most of the foreign exchange order flows are noisy, and done by rational speculators, this is an indication of manipulative action.

2.2.3.2.2.3 Cryptocurrency Markets

Li, Shin and Wang (2019) investigate pump and dump manipulation schemes in cryptocurrency markets in China, Russia and USA during May 2017 to August 2018. The study examines trading data from 500 distinct pump and dump schemes and 239 unique tokens. They find that pump and dump schemes generate short-term bubbles where prices, volume and volatility rise followed by reversals. The reversals imply that outsiders are unable to unwind their positions and consequently make losses. They also find significant evidence suggesting wealth transfer from outsiders to insiders of the scheme. Unlike other typical pump and dump schemes where manipulators buy the asset to pump the price up, uninformed speculators motivate the pump in the study by Lin *et al.*, (2019).

In an earlier study by Gandal, Hamrick, Moore and Oberman (2018) investigate suspicious activity on Bitcoin volatility during a 10 month period in 2013. They find that suspicious trading activity is highly correlated with the rise in the exchange rate of the Bitcoin. For example, they show that actions of 2 actors are connected with the daily 4 percent increase in price. Consistent with the study of Aggarwal and Wu (2006), they also observe a rapid fall in the price during the period after the suspicious activity.

2.2.3.2.2.4 Commodity Markets

Pirrong (2017) document evidence of market power manipulation in commodity markets. The survey finds that there were 124 incidents of manipulation between 1867 and 1921 in the USA prior to enactment of the legislation. The manipulations distorted prices and dented the perception of the market.

2.2.4 Summary of studies about price manipulation

These studies document evidence that manipulation occurs in different circumstances and various markets; namely, stock markets, derivatives and futures, cryptocurrency, foreign exchange markets and commodity markets. It also involves distortion of financial benchmarks such as the LIBOR. Distortion of prices harms market efficiency. Empirical research as provided by studies discussed earlier, shows that manipulation leads to temporary price impacts, increased volatility, large trading volumes, short-term price continuation and long-term price reversals (Huang and Cheng, 2015). These studies also show that individual stocks, indices, events, small capitalized firms, illiquid stocks or neglected firms, those with less float rate and/or high leverage ratio as well as those with high levels of information asymmetry are susceptible to manipulation (Aggarwal and Wu, 2006; Comerton-Forde and Putniņš, 2011a; Putniņš, 2012; Imişiker and Taş, 2013; Huang and Cheng, 2015; Imisiker and Taş, 2018).

Several studies show that manipulation is prevalent in emerging markets (Khwaja and Mian, 2005, Aggarwal and Wu, 2006, Putnins, 2012). These studies find that this is due to weak regulations, weak institutions and inadequate enforcement capacity. They show that there is dearth of empirical work that zeroes in on governance of market intermediaries due to limitation in data. Putniņš, (2012) posit that studies show that very little is known about price manipulation with respect to its frequency, impact and how regulation deters the practice. Kyle and Viswanathan (2008) argue that unless it is understood how manipulation techniques affect both pricing accuracy and liquidity, it remains challenging to determine the extent of damage on economic efficiency exacerbated by manipulation and so define such as inappropriate behavior. Put differently, many aspects are not well understood. The motivation that underpin stock price manipulation remains unclear. Literature is silent on the frequency of manipulative behavior. That said, price efficiency and liquidity are fundamental aspects of market quality (Comerton-Forde and Putniņš, 2011b). What is also lacking in literature is empirical evidence of price manipulation. Thel (1993) asserts that the only way to determine whether manipulation

actually takes place is through direct observation. However, Thel (1993) cautions that it is challenging, as manipulators hide their price-moving intentions. Evidence is therefore provided indirectly, through examination of prosecuted cases or examination of brokerage trading data. Putniņš (2012) posits that although manipulation distorts prices and harms resource allocation, the *ex-ante* effects remain unclear. It is not known how the possibility of manipulation affects prices and liquidity, and so, one cannot draw conclusion of overall harm caused by manipulation. Studies by Khwaja and Mian (2005) and Aaron *et al.*, (2018) find significant transfer of wealth from outsiders. Li, Shin and Wang (2019) confirms that pump and dump schemes are suggestive of heavy transfer of wealth. Sitko and Jayne (2012) find that potential for conflict of interest among the brokers and for manipulation in thinly traded agricultural commodity markets are some of the factors that impede trading and development of markets in African countries. Samuels, Yacout and Samuels (1981) posit that there are insufficient conditions to allow efficiency in financial markets in LDCs. For example, poor communication infrastructure, unequal availability of information breeds inequality in the manner the information is received and processed. This enables other groups to act on information swiftly than others. From a socio-political point of view, it can create unequal distribution of wealth. It is therefore important to investigate the extent to which misconduct by stockbrokers exists in LDCs. Regulators ought to be concerned if there are price distortions by their licensed market participants.

2.3 Disposition Effect

2.3.1 Definition and sources of Disposition Effect

Behavioral finance researchers such as Fama (1970, 1991) and Malkiel (2003) suggest that an individual behavior will on average deviate from the prediction of principles of rationality as exemplified by efficient market hypothesis and subjective expected utility. Shefrin and Statman (1985) study suggests that behavioral factors explain an investment bias termed disposition effect, a tendency to crystallize assets that appreciate in value too soon relative to assets that decline in value. The study argues that such behavioral factors are not explained by the rational model. Evidence of disposition effect has been documented by Lakonishok and Smidt (1986) and Ferris, Haugen and Makhija (1988) which show increasing volume for winner stocks relative to loser stocks in the USA stock markets. Further, Odean (1998) and Weber and Camerer (1998) also show that rational reasons do not explain disposition effect.

2.3.1.1 Behavioral explanations

There are many explanations of disposition effect that have been proposed in finance literature. Shefrin and Statman (1985) postulate the theoretical framework of disposition bias. The study contrasts a rational economic agent to an investor who is well aware of tax considerations for realizing gains or losses but is also affected by other elements which do not influence decisions of a rational economic agent. Shefrin and Statman (1985) state that first element that explains disposition effect emanates from the study of average behavior styled, prospect theory of Kahneman and Tversky (1979) study which argues that on average and in a world of uncertainty investors frame their choices in respect of gains and losses in relation to a reference point, typically purchase price. Then investors evaluate their choices by utilizing an S-shaped valuation function which is concave in the gains' region and convex in the losses region. This reflects risk aversion in the domain of gains and risk seeking in the domain of losses. Kaustia (2011) and Lehenkari (2012) state that an investor with preferences given by prospect theory will be more risk-averse after experiencing gains and more risk seeking after experiencing losses. This suggests that investors tolerate more risk as prices fall than otherwise. However, Barberis and Xiong (2009), Kaustia (2010) and Hens and Vlcek (2011) theoretical models on disposition effect argue that prospect theory does not explain disposition effect. For example, Barberis and Xiong (2009) theorise the relationship between prospect theory preferences and disposition effect. The study considers preferences which are construed as annual gains and losses on one hand and realized gains and losses on the other. They argue that unlike other standard utility theories, investors obtain utility from realized gains and losses. Using Odean (1998) methodology, they find that prospect theory preferences that are defined over annual gains and losses generally do not predict a tendency to sell winners and hold losers while preferences that are defined over realized gains and losses show more markedly that investors have a propensity to realize winners than losses. The distinguishing feature of their model is that for prospect theory preferences to explain disposition effect, they need not be confined to a fixed period e.g. a month or a year as doing so predicts the opposite of disposition effect. Thus, they argue that prospect theory explains disposition effect if an investor actually realizes the gains or losses unlike consideration for paper gains and losses.

Shefrin and Statman (1985) also explain that disposition effect emanates from mental accounting¹⁵, a tendency whereby investors assign sources and uses of funds into different

¹⁵ This concept was formulated by Thaler 1980, 1985, 1999 and Tversky and Kahneman 1981

mental accounts. For example, if an investor undertakes purchase of two different assets, they open different mental accounts and assign such investments. They then evaluate their performance by running a score, evaluating gains or losses with reference to their purchase price, individually without regard for possible interaction with other investments.

Barberis and Huang (2001) study an equilibrium firm-level returns to investigate how loss aversion (tendency to be more sensitive to losses than gains) and narrow framing (tendency to focus on narrowly defined gains and losses) influence the investor trading behavior. In their model of investor preferences, they utilise experimental data from USA from 1925 to 1995 to show how investors make choices amongst risky gambles. Their experimental evidence show that individual stock accounting explains stock returns. They also find that investor's mental accounting affects asset prices. As investors change their view of accounting for individual stocks to evaluate the overall portfolio, the mean value of stock returns declines, become less volatile and more correlated with other stocks in the portfolio. Their model predicts that investors who are narrow framers (as individuals investors) will sell stocks to arbitrageurs (institutions) in market troughs while institutions will sell to individuals at market peaks. The results of the Barberis and Huang (2001) model contradict the findings of Odean (1998) which documents that investors are reluctant to sell stocks with short-term prior losses preferring to sell prior short-term winner stocks. Barberis and Huang (2001) explain that investors preference over the horizon (time period) with which they accept and admit a loss determines their trading behavior. For example, over a short term, if a stock falls in price, an investor may not consider it as loss, and so prefer to hold hoping that it will bounce back to break even. If the stock experiences a sustained decline in price over long term, an investor may admit that there are nil chances of recovery and take a loss, viewing the stock as risky and sell it. Thus, while Odean (1998) attributes disposition effect to prospect theory, Barberis and Huang (2001) suggest that the time-period taken to admit a loss determines trading behavior.

Shefrin and Statman (1985) posit that the third behavioral explanation of disposition effect is regret aversion. The authors define it as an emotional feeling associated with a decision that turns out to yield undesirable result than an alternative ignored decision. The authors state that closing a securities account at a loss yields regret while closing it at a gain yields pride. Kaustia (2011) posits that closing an account at loss is equivalent to admitting a mistake which causes regret over a decision taken to purchase an asset. Recent theoretical arguments and experimental evidence suggest that the fear of regret that culminates into loss aversion may better explain disposition effect. For example, Thaler and Johnson (1990) document evidence

that a loss that is experienced after a prior gain is less harmful. On the other hand, they argue that a loss that is experienced after a prior loss is more hurting. They explain that investors are sensitive to additional setback and so hate losses.

Studies by Staw (1981) and Brockner (1992) suggest that the theory of entrapment or escalation of commitment explains disposition effect. Lehenkari (2012) documents evidence by investigating the explanatory value of commonly cited explanations of disposition effect namely prospect theory, belief in mean-reversion and escalation of commitment. The author makes an empirical comparison of competing explanations using detailed data from 1st January 1995 to 30th December 2003, on shareholdings and transactions of all individuals in the Finnish stock market. The difference with previous studies in the Finnish market such as Grinblatt and Keloharju (2001), is that besides analyzing stocks that are self-purchased by the investors, Lehenkari (2012) include stocks that have been gifted or inherited. The study argues that personal responsibility influences investor's decision to either sell or hold a stock. Lehenkari (2012) follows the methodology of Grinblatt and Keloharju (2001). While the study critiques the methodology, by arguing that it ignores the problem of unobserved heterogeneity which arises from within-individual correlation of observations or due to investor specific variables, Lehenkari (2012) addresses the challenge by incorporating investor- specific random effects into the modelling framework. However, computational hurdles affect their modelling and so incorporate few control variables which in the process renders their methodology less extensive than that of Grinblatt and Keloharju (2001). By undertaking the controls to distinguish self - purchased-stocks from inherited or gifted stocks, the study claims to isolate conditions under which each explanatory theory affects disposition effect.

Lehenkari (2012) finds that investors in the Finnish stock market exhibit realization of gains rather than losses, consistent with disposition effect. The behavioral bias is prevalent for stocks that are self-purchased than inherited or gifted stocks. This finding however questions the theory that prospect theory or belief in mean-reversion explains disposition effect. Lehenkari (2012) explains that escalation of commitment might be the reason why investors display disposition effect. This is because investors are gripped with fear of regret which is associated with realizing losses as well as unwillingness of admission that the initial investment decision was wrong. The second finding of Lehenkari (2012) contrasts the result of Grinblatt and Keloharju (2001) that state that disposition effect reverses as the year ends i.e. in December. Lehenkari (2012) findings also show that the belief in mean-reversion does not explain the relationship between personal responsibility and investors' decision making.

2.3.1.2 Rational explanations

Literature also suggests rational explanations for disposition effect. For example, Odean (1998) posits that investors exhibit disposition effect because of their belief in mean-reverting prices. Specifically, investors believe that current losers will outperform current winners. However, this appears to be at odds with the efficient markets, as the weak - form of the efficient market hypothesis (EMH hereafter) suggests that past prices cannot predict future returns. Odean (1998), and Weber and Camerer (1998) document evidence that contradicts the assertion of belief in mean-reverting prices.

Odean (1998) describe other rational reasons for investor's exhibition of disposition effect, namely portfolio rebalancing and avoiding transaction costs. Studies by Odean (1998) and Brown *et al.*, (2006) show that after controlling for rebalancing and share prices, disposition effect is still exhibited. In addition, it is observed that stocks that investors decided to sell eventually outperform the loser stocks that they hold.

Odean (1998) state that investors are cautious of high transaction costs. Evidence by study of Ferris, Haugen and Makhija (1988) show that investors are reluctant to crystalize losing stocks of already declining prices. This means that investor's behavior is consistent with value function of prospect theory and a belief in mean-reverting prices. Thus, Odean (1998) does not find empirical support for transaction costs as an explanation for disposition effect.

These studies suggest competing explanations of disposition effect arguing that it emanates from rational as well as behavioral factors. Behavioral factors include prospect theory explanations, mental accounting, regret aversion and theory of entrapment or escalation of commitment. On the other hand, rational explanations include belief in mean-reverting prices, portfolio rebalancing and avoiding transaction costs.

2.3.2 Empirical Findings

The initial studies about investor portfolio experience were documented by Schlarbaum, Lewellen and Lease (1978). The authors document evidence of rates of return realized by individual investors in the USA. The study deployed a questionnaire and analyzed securities transactions for 2500 brokerage house clients during January 1964 to December 1970. The primary finding of the study was that individual investors have superior securities selection abilities. However, later studies have contradicted this view. For example, in a comprehensive review Barber and Odean (2013) argue that individual investors underperform market

benchmarks because they have poor selection abilities amongst others. In addition, they do not hold diversified portfolios; overconfidently trade and incur unnecessary costs; get influenced by media and past experience; and tend to sell winners and hold losers in the process generating an avoidable tax liability.

Following the seminal work of Shefrin and Statman (1985), there has been a lot of empirical studies that investigate disposition effect such as Lakonishok and Smidt (1986), Ferris, Haugen and Makhija (1988), Thaler and Johnson (1990), Odean (1998), Weber and Camerer (1998), Heath, Huddart and Lang (1999), Genesove and Mayer (2001), Shapira and Venezia (2001), Grinblatt and Keloharju (2001), Goetzmann and Massa (2003), Kaustia (2004), Locke and Mann (2005); Coval and Shumway (2005); Feng and Seasholes (2005); Frazzini (2006), Choe and Eom (2009); Kim and Nofsinger (2007); Brown *et al.*, (2006), Dhar and Zhu (2006), Barber *et al.*, (2007), Calvet, Campbell and Sodini (2009), Kaustia (2010), Leal, Rocha Armada and Duque (2010), Seru, Shumway and Stoffman (2010), Lehenkari (2012), Frydman and Rangel (2014), Fischbacher, Hoffmann and Schudy (2017), and Muhl and Talpsepp (2018).

We group the empirical findings according to their empirical explanations including prospect theory explanations, tax-loss selling; price implications and studies about investors classes and sophistication.

2.3.2.1 Potential causes of disposition effect – Prospect Theory preferences

Studies such as Odean (1998), Weber and Camerer (1998), Barber *et al.*, (2007) and Lehenkari (2012) investigate potential causes of disposition effect. For example, Odean (1998) investigate the tendency to hold losing stocks too long and sell winning stocks too early and tax motivated trading in December during the period January 1987 to December 1993. By examining 10 000 accounts of a USA discount brokerage firm, the study develops a meticulous method of measuring disposition effect. The test involves calculating gains and losses against the stocks' original purchase price. It then computes the differences between realized gains and losses to assess whether an investor realized a profit or loss; and for the stocks that were held but not sold, paper gains and losses. The study documents evidence of disposition effect during the year except in December when investors were observed to realize losses at a higher rate relative to realizing gains. The study finds that there is a probability of 50 percent that stocks that witness price increases are more likely to be sold than those that register price declines. The study also finds that the average returns of winning stocks are 3.4 percent higher in the

following year than those of losing stocks. This means that investors' expectations that losing stocks outperform winning stocks does not hold. Odean (1998) findings suggest that prices do not revert to their mean. Similar findings have been reported by the study of Jegadeesh and Titman (1993) who find price momentum over the horizon of eighteen months. However, studies by DeBondt and Thaler (1985, 1987) have documented contradictory findings that reported price reversals for horizon of three to five years.

Odean (1998) explain that regret aversion may be the reason behind the disposition effect. The author also argues that due to tax benefits in the USA, investors postpone realizing gains in December. Odean (1998) demonstrates that portfolio rebalancing and mistaken belief in mean-reversion do not explain investors' behavioral bias to sell winners faster than losers.

Heath, Huddart and Lang (1999) investigate the relationship between psychological factors and decisions to exercise employee option in the USA over a 10-year period from August 1985 to December 1994. They examine how price movement affects exercise of options within 7 companies listed on NYSE and NASDAQ. They find that price trends influence the decisions to exercise employee options. They also find that employee decision to exercise is motivated by the relation between the current stock price, and a psychological reference point, often a stock price in the previous year. In addition, employees trading activity doubles when the stock price far exceeds the maximum price attained in the previous year. The study argues that employees have prospect theory preferences to move from risk seeking behavior at the time the options are granted to risk-averse behavior when the stock price far exceeds the maximum attained in the previous year. The observation that individual option holders react to past stock prices is consistent with psychological belief models, for example the study of Barberis, Shleifer and Vishny (1998) which models investor sentiment.

Thaler and Johnson (1990) investigate using experiments how prior gains and losses influence risk taking behavior. They test decision making process of university students in the USA. By making an assumption that prior outcomes generally affect decision making, they find that prior gains enhance the willingness to take more risks which they term "house money effect" while prior losses reduce the propensity to take risks. They argue that risk seeking (aversion) is observed after prior gains (losses) because successive gains (losses) are (not) integrated with the prior outcomes. If investors experience a small loss after prior large gain, then the loss is absorbed by the gain which influences loss aversion and enhances risk seeking behavior. In addition, the study also observes that people who have experienced losses may take risk if an opportunity to break-even is present. This is because investors vary a reference point and hence

the preference order of prospects. They also explain that after prior losses, risk seeking may be due to the fact that investors are motivated by the opportunity to return to an original position. These studies argue that prospect theory preferences explain disposition effect. This suggests that investors exhibit disposition effect when they are risk averse over gains and risk loving over losses.

2.3.2.2 Findings about disposition effect and tax loss selling

Ferris, Haugen and Makhija (1988) test tax-loss selling and disposition effect hypothesis using trading volume and price performance. Using USA empirical data from December 1981 to January 1985 for thirty small stocks by equity value, they deploy regression techniques to estimate abnormal turnover for stocks. They find that consistent with tendency to sell winners sooner than losers, disposition effect influences strongly the volumes traded at the year-end as well as during the year.

Lakonishok and Smidt (1986) investigate the relationship between abnormal volume and past prices. They examine investors' response to capital gains taxes. They use monthly prices and share volumes for listed companies on NYSE and ASE (USA) from 1968 to 1982. They deploy both parametric and non-parametric tests to determine if there were differences in the abnormal turnover of stocks that gained values and those that lost value. They find that volume is higher for winner stocks than for losers suggesting that tax incentives affect turnover, although they warn that it is not the only factor. Other factors such as diversification; amount of research attention given to a firm subject to its size; favourable information; and aversion to loss realization, also contribute to the correlation between prices and volume. The study does not find any evidence that turnover is influenced by changes in duration of investment necessary for qualification of long-term capital gains. Ferris, Haugen and Makhija (1988) and Lakonishok and Smidt (1986) explain that volume for shares whose prices have declined is lower than volume for stocks whose prices have risen because of the tax code which allows investors to use losses to offset gains and reduce their tax bill.

Booell-Gunesh, Broihane and Merli (2009) investigate the impact of tax regimes on the selling behavior amongst French investors during the period 1999-2006. Using the methodology of Odean (1998), they find that all groups of investors exhibit disposition effect. They find that investors are on average 60 percent more likely to sell stocks that have risen in value than those that have declined. In addition, investors are not influenced by the tax regime,

contrary to findings of Odean (1998) and Brown *et al.*, (2006). They also find that the level of sophistication does not eliminate disposition bias. They show that disposition effect is not motivated by the need to rebalance portfolios.

2.3.2.3 Disposition effect and investor classes

Disposition effect has been extensively studied among investor classes (Weber and Camerer (1998), Shapira and Venezia (2001), Brown *et al.*, (2006), Barber *et al.*, (2007), Leal, Rocha Armada and Duque (2010), Calvet, Campbell and Sodini (2009), and Choe and Eom (2009)).

Weber and Camerer (1998) investigate by experimental analysis and test directly for disposition effect by matching individual's trading decisions at prices at which they bought stocks. The experiment utilised a questionnaire other than a trading computerised software. The authors experiment with students from Germany, trade in six assets over 14 periods. The students use Bayes rule to update their probabilities based on observed price movements. They find that students tend to realize losses fewer than they realized gains. In addition, the participants sold very few shares when the price fell below the reference point than when it rose above it. This suggests that multiple reference points affected how they framed and decided on their investment choices. Weber and Camerer (1998) observe that disposition effect hurts investors profits. In the experimental design, the falling prices showed a declining trend implying that a sell decision should be made while rising prices depicted an upward trend implying a decision not to sale. However, the students traded contrary to the study design by selling rising stocks and holding losing stocks. The results support the findings of Shefrin and Statman (1985) and Odean (1998). Weber and Camerer (1998) explain that using prospect theoretical preferences, the students use the purchase price as a reference point to recognize gains and losses; and are reluctant to recognize losses. Consequently, they keep losers and sell winners. The authors also explain that the students do not perceive correctly the probabilities of future price changes i.e. they think that losing stocks will bounce back while winning stocks will decline.

Barber *et al.*, (2007) conduct an empirical analysis of the tendency to sell winners at a faster rate rather than losers by an individual and aggregate investor. The authors analyze all investor trading activity in Taiwanese market from January 1995 through December 1999. They examine over a billion transactions by almost four million traders. They use the methodology of Odean (1998) to measure disposition effect. However, they enhance the methodology by

computing gains and losses for all calendar days unlike Odean (1998) study which considered days on which stock sales occurred. Barber *et al.*, (2007) find that generally, Taiwanese investors, individually and in aggregate tend to sell winners and hold losers. The results show that 85 percent of investors are roughly twice as likely to sell assets whose prices have risen than those whose prices have declined. Specifically, Taiwanese investors realize losses at a daily rate of 1.4 percent compared to gains at 2.9 percent. This means that losses are realized at approximately half the realization rate of gains.

Barber *et al.*, (2007) also find that investors realize gains at a higher rate than losses on 87 percent of days analyzed. The daily turnover rate for gains exceeds that of losses. Specifically, the proportion of gains realized exceeds the proportion of losses realized. This means that the evidence is consistent with the notion of reluctance to crystallize losses. The study also finds that individual investors, corporations and dealers exhibit disposition effect while domestic mutual funds and foreign investors do not.

Choe and Eom (2009) investigate disposition effect in Korean stock index futures market. Using a dataset for the period January 2003 to March 2005, examining 69,391 different investors over 22 million transactions, they deploy the methodology of Odean (1998). However, the study varies the methodology slightly to measure disposition effect as the difference between investors propensity to realize gains and their propensity to realize losses. They determine gains and losses by comparing the current futures price to the contract weighted average open-buy or open-sell price. The study finds that generally all investors exhibit disposition bias. However, individual investors are more prone to disposition bias relative to institutional investors and foreigners. For example, the mean difference of the disposition effect in a specific account is 0.078 which implies strong tendency to realize gains than losers. They find that on average investors realise smaller gains and hold onto large losses.

Choe and Eom (2009) also finds that there is a negative relationship between disposition effect and the proxies for trading experience or investor sophistication. This supports the hypothesis that professional investors are less prone to disposition effect. The findings are consistent with evidence of Feng and Seasholes (2005) and Dhar and Zhu (2006) whose results suggest that sophistication and experience reduces disposition effect. Finally, Choe and Eom (2009) find that there is a negative relationship between disposition effect and investor performance (profits). This confirms that hypothesis that disposition bias is costly in line with Odean (1998) and Coval and Shumway (2005).

Grinblatt and Keloharju (2001) investigate the motivation for trading activities. The study analyzes several behavioral and economic effects to ascertain their effect on trading activity. They examine data from all Finnish investors (both retail and institutional) during the period 27th December 1994 to 10th January 1997. They screen over one million buy and one million sell transactions that translate into 293 034 binary data points. They specifically examine the relationship between disposition effect and past returns. Using logit regression estimated with maximum likelihood procedures, they examine extreme capital losses of more than 30 percent, moderate capital losses of less than 30 percent, capital gains and those with zero returns. They consider several controls for effects that arise due to omission of other variables. They find evidence consistent with crystallization of large gains and reluctance to crystalize large losses. This is consistent with the theory of disposition effect. Like Odean (1998), the authors also find evidence that tax loss selling is prevalent in December, particularly in the last two weeks. The findings of Grinblatt and Keloharju (2001) suggest that motivation for trade is related to recent returns. However, they observe that experienced investors do not rely heavily on past returns to make buy or sell decisions. The less experienced investors, mostly individuals place a lot of weight on past returns, hence displaying a contrarian behavior. On the other hand, they find that foreign investors display momentum investment strategies

Kaustia (2010) investigate the relative importance of prospect theory and other explanations for the disposition effect. The study uses data from Finland for all household investors from January 1995 to May 2000. Like Grinblatt and Keloharju (2001), they use logit regression, with dependant variable as decision to sell, versus to hold a stock. The independent variables are indicators for the holding period capital gain/loss over various ranges. Then the regressions are run for different holding periods and include a number of control variables such as past returns. The only difference with the study of Grinblatt and Keloharju (2001) is the duration of the sample period, which is 5 years. The study finds that contrary to the prediction of prospect theory, which predicts that the tendency to sell will decline as gains or losses increase, empirical evidence shows that the tendency to sell an asset does not decline as gains or losses increase. Kaustia (2010) specifically find that over holding periods of 1 year to 3 years, the tendency to sell actually increases or is constant in the domain of gains and is not responsive over a wide range of losses. Kaustia (2010) also find that consistent with the motivation to lock in capital gains for price increases of over 70 percent or 100 percent, investors are reluctant to sell. The results of the study are complemented by findings of Barberis and Xiong (2009) which state that the prospect theory cannot explain the frequency of realizing gains and losses in

Odean (1998) study. Barberis and Xiong (2009) argue that if paper gains and paper losses are ignored, then investors would derive prospect theory utility that would predict the disposition effect. Although Kaustia (2010) support psychological explanations for disposition effect, the study does not provide conclusive tests for validity.

Calvet, Campbell and Sodini (2009) comprehensively investigate the dynamics of household portfolios in Sweden from 1999 to 2002. They examine determinants of selling decisions. They find that absolute value of returns positively influences the household selling decision. The effect is stronger for stocks whose prices have risen in value than those which have declined. The study also investigate the relationship between selling decisions and portfolio rebalancing. They find that households deploy few trading strategies by engaging in risk-seeking behavior when their portfolios underperform. When their portfolios perform better, they rebalance by full selling of winner stocks implying risk-aversion. These findings are consistent with the disposition effect.

Calvet, Campbell and Sodini (2009) also find that households which are wealthy and have diversified portfolios exhibit lower disposition effect. This slightly varies from the findings of Dhar and Zhu (2006) which finds that income level influences the strength of disposition effect. The study by Calvet, Campbell and Sodini (2009) argues that wealth and diversification are influential in reducing the extent of disposition effect than mere level of income which Dhar and Zhu (2006) study suggests.

Brown *et al.*, (2006) examine disposition effect among investors in initial public offering (IPO hereafter) stocks in Australian stock market from 1995 to 2000. Using Odean (1998) measure, they analyze the investors trading behavior. They also test the hypothesis of ‘house-money effect’ of Thaler and Johnson (1990) which predicts that increasing risk -seeking behavior following previous gains and a tendency towards ‘breaking-even’ following experiencing losses.

Brown *et al.*, (2006) find that Australian investors display disposition effect except in the month of June, which is the end of tax year, where disposition effect is reversed due to tax loss selling by most investors apart from those exempted from tax and foreigners. The IPO investors have a tendency to realize 1.03 percent of their gains compared to 0.66 percent of their losses with a PGR/PLR ratio of 1.58. An examination of index stock investors show a 0.66 percent for gains and 0.33 percent for losses with a PGR/PLR ratio of 1.99. They also find that the behavioral bias wanes over time as the number of trading days goes beyond 200 days. They

also document evidence that supports the house money effect. They find strong evidence that investors cushion losses with previous gains and when they experience losses, they engage in risk-seeking behavior motivated by the spirit to break even when opportunities exist. They explain that narrow framing accounts for investor's behavior in line with the study of Barberis and Huang (2001). They also find that shareholder loyalty schemes which are designed to motivate investors to retain their holdings influences minimally the tendency to sell winners.

Several other studies document presence of disposition effect among investor classes such as Shapira and Venezia (2001), Feng and Seasholes (2005), Dhar and Zhu (2006), and Leal *et al.*, (2010). Shapira and Venezia (2001) document presence of disposition effect amongst individual stock market investors. The authors analyze investment patterns of both individual and professional investors. The study utilizes one-year data (1994) from the Israel stock market. The authors utilize the methodology of Schlarbaum, Lewellen and Lease (1978) which tests for disposition effect by comparing the duration of losing round trips¹⁶ to winning round trips. Shapira and Venezia (2001) find that independent stock market investors and those that are advised by brokers in Israel exhibit disposition effect. Specifically, the study finds that the average duration of a losing round trip relative to winning round trip was 55 days to 25 days for professionals and 63 days to 20 days for individuals. This means that individuals took longer to crystalize losses than professionals. The study also finds that an average duration of the losing round trips is significantly longer than winning round trip for both groups, suggesting that both groups of investors exhibit the tendency to hold losers too long than winners. This finding is consistent with disposition effect. The study also analyzes behavioral patterns in the type of round trips namely simple and sequential. Simple rounds are those involving one buy and one sell order while sequential deals involve more than one sale or buy trades. They test for difference in disposition effect between the groups (individuals and professional group) and find that disposition effect largely emanates from simple rounds relative to sequential rounds. This means that short term traders exhibit disposition bias.

Leal *et al.*, (2010) investigate the extent of disposition effect among individual investors in Portuguese stock market from 1st January 1999 to 31st December 2002. They examine investor trades of 1496 clients totalling 159 406 trades. They find strong evidence of disposition effect among individual investors throughout the year, suggesting that investor's preferences are not influenced by fiscal effect. They find that propensity to sell winners in December is 3 times

¹⁶ Shapira and Venezia (2001) define round trips as transactions where there is a buy trade and a subsequent sell trade at the end of the round such that the client has a zero position in the stock.

higher than the propensity to sell losers, and even higher than the rest of the year. This contradicts the findings of Odean (1998) and Brown *et al.*, (2006) which do not find disposition effect at the end of tax year. They also find that disposition effect in different market conditions, however it is more evident during the bull market than in the bear market. The differences between the periods is statistically significant. Using the criterion of frequency of trading, high volume of transactions and high portfolio value as proxy for sophistication, they find that sophisticated investors display lower disposition effect than less sophisticated investors.

Although studies such as Grinblatt and Keloharju (2001), and Barber *et al.*, (2007)) document disposition effects among individual investors other studies such as Boolell-Gunesh, Broihanne and Merli (2009) do not find that disposition effect is sensitive to investor type.

2.3.2.4 Disposition effect and Price Implications

Frazzini (2006) tests whether disposition effect induces underreaction to news, leading to return predictability. The study argues that a large subset of investors who display disposition effect can generate stock price underreaction to news which in turn creates return predictability and post announcement price drift. The author tests the hypothesis that presence of disposition effect hampers the transmission of information when the firm specific information such as earnings announcement is released, thereby inducing a predictable price drift. The drift depends on the news content (positive or negative) and the difference between the current and the reference price. Using data from 29812 mutual funds in the US from January 1980 to December 2002, they find that disposition effect can induce underreaction to news leading to return predictability and post announcement drift. In addition Frazzini (2006) documents that managers of underperforming mutual funds are reluctant to close their losing positions while successful managers realize losses at higher rates than gains. This suggests that less successful managers are prone to disposition effect. They are 1.7 times more likely to realize gains than a paper loss.

Locke and Mann (2005) investigate the relationship between futures traders' discipline (speed of executions and avoidance of riding losses) and tendency to exhibit disposition effect. They specifically examine trader's behavior among 300 futures traders at the Chicago Mercantile Exchange (CME) in USA during the period 1995. They deploy the methodology of Odean (1998) to measure disposition effect. The study finds that futures traders who offset losses within 10 minutes are more likely to be successful in future while those who hold onto

significantly large losses longer are less likely to be successful. They also observe that the speed at which they lock in gains predicts traders' success. They explain that the findings are not connected to loss aversion but rather a rational behavior. They argue that as the reference point varies from zero benchmark to expected profit, the strength of disposition effect disappears.

Coval and Shumway (2005) document evidence that futures traders who register midday losses subsequently take excessive risk and show suboptimal performance in the later part of the day. The study shows that morning suboptimal traders are 31.2 percent more likely to take above average risk in the later part of the day compared to an optimal trader who has a 27 percent chance of taking risk. Specifically, suboptimal trading account for 38 percent of all afternoon market trades. Both studies, Locke and Mann (2005) and Coval and Shumway (2005) find disposition effect amongst futures traders. However, Locke and Mann (2005) does not attribute presence of disposition effect to loss aversion. They argue that rationality explains why traders cut losses early during trading, consistent with the theory of Hens and Vlcek (2011) which model a financial market where a small individual investor is faced with two portfolio choices, namely a bond and a stock. Hens and Vlcek (2011) deploy a binomial process using parameters namely myopic loss aversion, decision weighting and asymmetric risk taking to investigate investor risk taking behavior when the stock price rises and when it declines. They focus on *ex-ante* disposition effect where besides requiring an investor to sell winners and hold losers they require an investor to buy the stock in the first period. They find that prospect theory does not explain *ex-ante* disposition effect, however it does explain *ex-post* disposition effect. They argue that prospect theory assumes that investors bought a stock in the first place, but this may not obtain, such that the prospect theory is an after-the-fact argument.

O'Connell and Teo (2009) investigate disposition effect in the currency market. They examine data from a US based custodian ranging from 1 January 1994 to 31 December 2002. The study adopts the methodology of Odean (1998), and so compares the proportion of losses realized (PLR) with the proportion of gains realized (PGR). They also utilise the methodology of Grinblatt and Keloharju (2001), logistic regression. They do not find disposition effect among large institutions. The findings show that institutional investors increase risk-taking following gains and minimise risk seeking behavior following losses, consistent with evidence from gambling experiments of the study of Thaler and Johnson (1990). These findings contradict Grinblatt and Keloharju (2001), Locke and Mann (2005), and Coval and Shumway (2005) who find disposition effect amongst professional traders. O'Connell and Teo (2009) argue that the

sophisticated investors in their sample do not exhibit disposition effect due to dynamic loss aversion that explain predictability amongst others.

The studies of Coval and Shumway (2005), Frazzini (2006), and O'Connell and Teo (2009) document that behavior biases have implications for efficient markets since future returns are influenced by past prices.

2.3.2.5 Disposition effect and Investor characteristics - sophistication and trading experience

Various studies investigate the relationship between investor characteristics and disposition effect. They examine how disposition effect may be attenuated (Dhar and Zhu (2006), Feng and Seasholes (2005), Seru, Shumway and Stoffman (2010), Frydman and Rangel (2014) Fischbacher, Hoffmann and Schudy (2017)). For example, Dhar and Zhu (2006) show that certain investor characteristics reliably predict the tendency to engage in disposition effect. The study investigates the relationship between investor sophistication and disposition effect across individual investors. The authors examine trading records of a big discount brokerage firm in the USA, from 1991 to 1996 covering over 50 000 individual investors. The study utilises differences in trading frequencies and demographics to proxy knowledge about investments. They document empirical evidence that wealthier individuals and employees in professional occupations are less prone to disposition effect. They also find that trading frequency attenuates disposition effect. They specifically find that financial literacy factors such as income and occupation status lower the tendency to realize gains faster than losses. The disposition effect of the more knowledgeable is between 10 to 20 percent smaller than those who possess less investment knowledge. Further, the more knowledgeable are 18 to 50 percent less likely to exhibit disposition bias. This means that the level of financial literacy affects the degree to which they exhibit disposition effect.

Feng and Seasholes (2005) investigate whether investor sophistication and trading experience reduce disposition effect among Chinese investors. They examine individual brokerage accounts from the date of opening on 1st January 1999 through their lifecycle. The study ably follows an investors' trading behavior relative to measuring average effects for a group of individuals. They deploy logit regression and survival analysis, a statistical model which according to Feng and Seasholes (2005) describes how investors typically hold a stock position before selling, to test for disposition effect. They find that sophisticated investors are 67 percent less likely to exhibit disposition effect. They also find that sophistication and experience

minimise the realization of gains by 37 percent but does not totally eradicate the disposition to realize gains.

Seru, Shumway and Stoffman (2010) examine attrition within Finnish household data to investigate if investors learn about their ability. The empirical data covers the period 1995 to 2003. They find empirical evidence of learning by investors. Specifically, investors who underperform are more likely to quit trading if their returns are one standard deviation from the mean return. They also find that after executing over 100 trades, investors earn an average return of 3.6 basis points over 30 day horizon and register a decline in tendency to sell winners more than they sell losers by about 2 percent. This shows that disposition effect declines with experience while performance improves due to experience. The study suggests that investors learn by trading.

Frydman and Rangel (2014) investigate whether the disposition effect can be reduced by manipulating the saliency of the purchase price in an experimental stock market. The study uses laboratory experiments and categorise the subjects into two groups. One group is termed a high saliency group, and has a purchase price displayed on an online trading platform while the other group has its explicit reminders of purchase price removed. The subjects trade in three stocks in two sessions over 108 trials and 109 trials respectively. They find that individuals who were exposed to the stocks' purchase price exhibited disposition effect while the other group that had a less salient purchase price information registered a 25 percent decline in disposition effect. This suggests that a nudging approach may minimise behavioral bias in individuals.

Fischbacher, Hoffmann and Schudy (2017) investigate whether automatic selling devices (stop-loss and take-gain orders) relate to disposition effect. Specifically, they examine theoretical effects that causally reduce the disposition effect. Using an experimental approach, over February and April 2015, the investors which comprise of 72 students from University of Konstanz, are placed in 3 different groups to trade in six different assets. The groups have varying conditions with freedom to actively sell assets; in addition to condition in group one, sell assets by using automatic stop loss and take gain option; and to in addition to actively sell, be reminded when the limit is attained and decide whether to go ahead to sell or not. The study utilise the methodology of Odean (1998) to measure disposition effect. However, they compare the reference price with the study of Weber and Welfens (2007) where they use quantity of the weighted average purchase price as a reference point.

Fischbacher, Hoffmann and Schudy (2017) provide experimental evidence that low disposition effect exists in the group of subjects which uses automatic selling devices to effect stop- loss or take- gain orders, relative to the control group, and a third group where subjects have power to override alerts to take selling decision. They explain that this is because the subjects have an opportunity to decide to accept their forecasted losses. In other words, the subjects are psychologically prepared to accept forecasted losses.

Fischbacher, Hoffmann and Schudy (2017) also find that automatic selling devices help investors to increase the proportions of losers realized but did not affect the proportion of winners realized. The asymmetry impact from the limit treatment on disposition effect suggests that time-inconsistent behavior matters for disposition effect. This shows that unlike stop-orders, take-gain orders do not allow investors to commit postponing gains. The finding is consistent with a preference-based explanation for disposition effect that include time-inconsistent behavior. The study argues that the ability to commit in advance of executing a trade by selling at a specific price in future is challenging to imagine that it is influenced by belief. Like Frydman and Rangel (2014) study which proposes reducing saliency of purchase price, the findings of Fischbacher, Hoffmann and Schudy (2017) suggest that investors can decide to take selling decisions before price becomes known. However, the authors argue that a rational time consistent agent can forecast losses caused by automated sale and decide against realization.

These studies suggest that disposition effect may be attenuated by trading experience, a combination of sophistication and experience and a nudging approach. However, contradictory study by Boolell-Gunesh, Broihanne and Merli (2009)) finds that that the level of sophistication does not eliminate disposition bias.

2.3.2.6 Disposition effect and market conditions

Kim and Nofsinger (2007), Leal, Rocha Armada and Duque (2010) and Muhl and Talpsepp (2018) investigate the relationship between market conditions and disposition bias. For example, Kim and Nofsinger (2007) document empirical evidence about how investor trading behavior is influenced by market conditions. The study examines trading behavior of Japanese investors for 22 906 stock-years of data, from 1984 to 1989, a bear period and 1990 to 1999, a bull period. The authors use portfolio sorting technique to analyze investor preferences; and regression techniques to estimate the relationship between individual ownership and variables

such as volatility and abnormal returns. They find that individual investors prefer to hold riskier stocks during the bear market than bull market. This suggests that investors have an asymmetric attitude towards risk. The study explains that this could be due to how investors perceive risk and their aversion towards risk. The study also provides empirical evidence that individual investors underperform in both states. For example, the estimate for abnormal return during the bull market is -0.016 while for bear market is -0.004, suggesting no significant change in performance in either state of the market.

Muhl and Talpsepp (2018) investigate the relationship between market conditions and disposition effect. Using a dataset from Estonian stock exchange for the period 1st January 2004 to 31st October 2010, they examine disposition effect by a methodology namely survival analysis, to predict an average period that a stock will be held. The focus of the study centers on how market conditions affect learning in relation to the disposition bias. Using survival analysis to predict the average period that a stock will be held by an investor, they find evidence that investor's exhibit marked disposition effect during either a bull or bear period. The disposition effect is stronger during a bear period. The study shows that as investors gain experience, they learn to overcome the bias. For example, frequent traders who are considered experienced, in their 101st trade tend to sell stocks with a loss that is 58 percent higher than that of investors with minimal trading frequency. The study states there is a reduction of 36 percent in the probability of an investor selling winning stocks. The study suggests that different market conditions are an important explanatory source of investor behavior. It also highlights challenges for inexperienced investors. The study shows that inexperienced investors not only suffer from marked disposition bias and show underperformance in relation to the overall market, but have significant problems in overcoming the bias when accumulating only limited experience (i.e. as they learn), particularly in a bear period.

2.4 Institutional Herding

2.4.1 Theoretical background

2.4.2.1 Definition and Sources of herd behavior

2.4.2.1.1 *Definition*

Since the birth of Behavioral Finance in the 1980s, researchers have extended the study of human behavior from individual perspective to forms of collective behavior of investors in the market. One such form of collective behavior is herding. Hirshleifer and Hong Teoh (2003) define herding as a behavior that stems from interactive observation of individuals. This

phenomenon originates from psychological studies which state that individuals vary their attitude (beliefs or belief system) if they are part of a group, motivated by their interaction and observation among the members of the group. A typically example would be a crowd running riot during demonstration against certain political decision whereby individuals vandalize property which they would not on their own as individuals. This crowd behavior also manifests in the financial markets, as it is a place where investors interact and observe each other. Herd behavior is well documented in finance literature. Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) theoretical studies define herding as a group of investors who ignore their own information and beliefs and choose to follow the decisions of others investors even when their information suggests a different course of action. Nofsinger and Sias (1999) describe herding as the trading in the same direction by a group of investors for a period of time. These studies generally defined it as mutual imitation leading to a convergence or correlated pattern of action.

2.4.2.1.2 Sources of herding

Finance literature explain varying sources of herding. Other researchers argue that herd behavior is based on fundamental information and stabilizes asset prices by incorporating new information into prices (i.e. it is rational) while other argue that it is not based on fundamental information and drives prices away from fundamental values (i.e. it is behavioral). Given these two opposing views about herding and its impact on asset prices, there has been a lot of research on this area, both theoretically and empirically regarding what potentially explains herd behavior. The schools of thought span from behavioral, informational and agency explanations.

Bikhchandani and Sharma (2000) differentiates intentional herding from spurious herding. The study states that intentional herding arises from an obvious intent by investors to imitate the behavior of others while spurious herding results from a scenario when groups facing similar decision problems and information sets end up taking similar decision. For example, if the central bank raises interest rates, investors will move their assets from the equity market to deposit with banks. In intentional herding, if an investor A bought an asset k in quarter 1, and obtains a higher return than investor B who did not buy the asset as part of their portfolio, then having learnt that investor A bought in the last quarter, investor B will follow suit to buy asset k . Researchers have an interest in intentional herding as it is understood from literature that investors often disregard their own private information to imitate the actions of other investors.

There are various explanations from psychological studies such as Barberis, Shleifer and Vishny (1998), Buckner (1965), Daniel, Hirshleifer and Teoh (2002) and Hirshleifer and Hong Teoh (2003) that state that herd behavior is associated with conservative bias and representative heuristic, rumour heuristic and limited attention.

Finance theory suggests that investor behavior is largely influenced by psychological biases¹⁷ and heuristics. One of the investor biases that finance literature suggests is contagion, a phenomenon driven by flow of information and investor beliefs. Investors are at ease when they observe and take investment action that has been taken by others. Hirshleifer (2001) construes this phenomenon as conformity. Conservatism and representative heuristic (Barberis, Shleifer and Vishny 1998) are also factors that literature suggests prompt herd behavior.

Buckner (1965) suggest that herd behavior may be driven by rumour-heuristic. It is argued in literature that investors may be influenced by rumours through interaction or media sources. Often, rumours are inaccurate. Further, Fung and Hsieh (2002) state that the speculative trading of hedge funds and consequent destabilizing action has been put to question.

Daniel, Hirshleifer and Teoh (2002) and Hirshleifer and Hong Teoh (2003) state that investors suffer from limited attention such that they tend to pay attention to more familiar and salient events amidst a web of information. Consequently, their investment decision making is influenced by such salient factors ahead of critical information. For example, investors may take an investment action guided by the fame of an analyst even when accurate information is against the analyst recommendation. Taking investment decisions requires analysis of fundamental information. It is costly in terms of time and financial resources to process investment decisions. Hence those who do not have the information skills or the information itself choose to mimic the decisions of others. Free-riding on the investment decisions of other investors potentially results into a correlated pattern of trading.

Given the importance of information in investment decision making, information asymmetry has been recognised as a potential source of herd behavior. It is often termed as information cascade. It occurs when investors infer information from each other's trades. Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) state that it occurs when investors disregard their own private information about stocks or the market and instead take decisions by observing others. Explained differently, it occurs where information provided by previous

¹⁷ Psychological impediments that affect human behavior and drives them away from rational expected behavior.

decision maker takes precedence over a given decision makers' private information to an extent that following a series of similar decisions, subsequent decision makers take a similar decision regardless of their private information. For example, an analyst may investigate a company's stock and arrive at a decision to buy the stock. He then observes that a group of investors have taken a decision to sell the stock. The analyst does not have access to the groups' private information and so treats the market signals, in this case the decision to sell by many others as more powerful than his own private information. He then takes a decision to sell the stock. Other investors will also consider this as even more signals and consequently take a selling decision. This will translate into a cascade that results in the value of the stock declining. Gavriilidis, Kallinterakis and Ferreira (2013a) state that when analyst ignore their own information and mimic the decisions of others, their information is not channelled by their actions to observers in the market. This behavior leads to a temporary blockage of information signals into the price setting mechanism and so consequently leads to market information inefficiency.

There are several reasons why informational cascades occur among investors. First, it may be possible that investors may know that their information is mediocre and therefore free ride on other investors' information, which they believe to be better. Literature suggests that analysts are likely to follow the direction of the leading analysts (Welch 2000). Second, it may be the case that investors find it very expensive to access credible information compared to less expensive way of mimicking the investment decisions of others.

Information cascades are an extreme case of information blockage. Lin, Tsai and Sun (2009) state that information cascades are a significant cause of herding. Given that efficient markets assume that price reflect full and available information, it means therefore that taking action different to what own information suggest implies a negative effect of information cascades on price or market efficiency. Besides informational explanations of herding, it is also posited in literature that the principal-agency problem between the employer (asset management firm) and their employee (i.e. investment/fund managers) may explain herd behavior in financial markets. Research shows that investment managers do not deviate from the market consensus for professional reasons, in order to protect their own interests. They thus place their interests ahead of client's best interests. Since the performance of investment managers is evaluated relative to their peers, there is a tendency to trend towards the market consensus. Thus for professional reasons they engage in herd behavior. Scharfstein and Stein (1990) show that

investment managers tend to follow a market trend because it is safer for professional reasons since a lone mistake is costly than a market's loss.

The other source of herding is reputational concerns which leads to reputational herding. Theorists have argued that reputation herding occurs when institutional investors disregard their own private information and opt to imitate the investment decision of others because they are afraid of making a wrong decision that will be different from the crowd. They would rather follow the herd and make a wrong decision than make a costly wrong decision that varies from that of the crowd. Scharfstein and Stein (1990) model show that institutional investors herding results from reputational concerns. They argue that such herding may be considered rational because the errors in prediction are not made alone but are shared with the crowd. Supporting evidence has been documented by Trueman (1994) which shows that analysts have a tendency to release forecasts that are similar to their peers than what their own information suggests. The study specifically shows that less skilled analysts have the tendency to herd towards earnings prediction of leading analysts. Additional evidence is documented by Graham (1999) whose reputation based model of investment newsletter recommendations show that analysts forfeit future gains for reputation concerns.

Finance scholars also suggest that the assumption of relative homogeneity of professional investors in relation to the rational paradigm of efficient markets as a possible source of herd behavior. They argue that professional investors share common features that may translate into behavioral conformance. For example, investment managers attain relatively similar educational training. This equips them with tools and techniques that enable them evaluate investment opportunities and lead to an investment action in a manner that a great number of those possessing such similar skills are likely to take. Thus they are likely to behave in a conformative manner, not necessarily by design. Further, the remuneration incentive is likely to push them towards conformance.

There is also an additional perspective regarding professional investors which suggests that they tend to trade in stocks with certain common characteristics. Falkenstein (1996) states that professional investors have a tendency to pick stocks that have common characteristics such as size, industry or past performance. The tendency of investors to be attracted by common characteristics leads to characteristic herding. The support to this theory is documented by the studies of Nofsinger and Sias (1999), Gompers and Metrick (2001), Bennett, Sias and Starks (2003) and Sias (2004). Researchers such as Holmes, Kallinterakis and Ferreira (2013) suggest

that since relative homogeneity and common characteristic lead to behavioral conformance, this type of behavior is construed as unintentional herding.

2.4.2.2 Intentional versus Spurious herding

In this section, we discuss whether intentional herding may be separated from spurious herding. Bikhchandani and Sharma (2000) distinguishes intentional herding from spurious herding. They explain that intentional herding results from an obvious intent by investors to copy the behavior of others. In addition, Stavroyiannis and Babalos (2015) suggests that intentional herding arises when investors ignore their own information and deliberately copy the actions of other investors who they believe to possess better information than them.

Regarding spurious herding on the other hand, Bikhchandani and Sharma (2000) explain that it occurs where groups facing similar decision problems and information set take similar decision. They further state that such similar decision taking is an efficient outcome. Stavroyiannis and Babalos (2015) define spurious herding as a market-wide homogenous reaction to readily available information and signals. Furthermore, Gavriilidis, Kallinterakis and Ferreira (2013a) state that spurious herding is common amongst investment professional traders since they utilise common factors (education, investment strategies, common regulatory environment) to arrive at an investment decision.

While Bikhchandani and Sharma (2000) differentiates intentional herding from spurious herding theoretically, they state that separating intentional herding from spurious herding empirically is impossible given that investment decisions are influenced by numerous factors. They state that spurious herding which is typically driven by fundamentals is not “herding” because investors are not changing their investment decisions due to imitation. The authors explain that investors are reacting to commonly known public information. While there are studies in literature that claim to correct for fundamentals, Bikhchandani and Sharma (2000) state that it is difficult to do so due to challenges in exactly defining what constitutes fundamentals or challenges in measuring and quantifying the fundamentals. Earlier studies that examine institutional herding such as Lakonishok, Shleifer and Vishny (1992) and Grinblatt, Titman and Wermers (1995) investigate herding at the stock level and rule out spurious (unintentional) herding but not true (intentional) herding. They document very little evidence of herd behavior amongst pension funds and mutual funds respectively. Holmes, Kallinterakis and Ferreira (2013) study first attempted to distinguish intentional from spurious herding. The

authors examine monthly holdings of Portuguese funds and document evidence of intentional herding, which is related to market conditions such as returns, volatility and regulatory changes. They explain that institutional herding is due to reputational reasons consistent with the theory of Scharfstein and Stein (1990). Gavriilidis, Kallinterakis and Ferreira (2013a) examine intentional institutional herding among Spanish funds at industry level after controlling for states of the market such as returns, volatility and volume. They document evidence at both market level; and at an industry level during periods of low market returns, high volatility and high volumes. They claim that their finding signifies intentional herding and explain that it is motivated by informational and career concerns. Using aggregate market data, Galariotis, Rong and Spyrou (2015) utilise known return factors such as size, book to market and momentum to isolate critical fundamental information and decompose cross sectional standard deviations to deviations due to reaction to fundamental information and deviations due to intent. They find that US investors herd motivated by both fundamental information and non-information during crisis period while UK investors herd due to fundamental information.

Other studies document spurious herding. For example, Guo, Holmes and Altanlar (2020) develop and test competing hypothesis to determine whether institutional herding is spurious or intentional. They examine influence of analyst recommendations and investment sentiment on trading behavior to determine whether institutional herd behavior is spurious or intentional. In their analysis, Guo, Holmes and Altanlar (2020) classify responding to correlated information related to analyst revisions or sentiment as spurious herding while responding primarily by reputational reasons or beliefs that other investors have better information as intentional herding. Using Sias (2004) methodology they document strong support that herding is spurious and find little evidence that it is intentional. They specifically find that institutional investors extract information from the revisions of the analyst recommendations. They explain that institutional investors herd consistent with investigative herding i.e. as a result of analysing the same information from the analyst revision recommendation indicators other than merely following the trades of others which they believe to be better informed.

It is clear in literature that although the study of Bikhchandani and Sharma (2000) argues that it is challenging to separate intentional from spurious herding, recent empirical studies by Holmes, Kallinterakis and Ferreira (2013), Gavriilidis, Kallinterakis and Ferreira (2013a) and Galariotis, Rong and Spyrou (2015) claim to attribute institutional herding to either intent or document spurious herding due to investors extracting common information. Further, studies

such as Guo, Holmes and Altanlar 2020) claim to identify spurious herding. Thus, we note from recent literature that researchers attribute herding to either spurious or intentional herding depending on whether they are able to identify common information among investors or lack of information, respectively.

2.4.3 Empirical Findings

The seminal work on herding is attributed to Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992). These studies proposed various explanations of herd behavior notably professional/career concerns and psychological reasons. The contemporary literature has empirically tested for herding in different market settings, at institutional investor perspective using micro-models (portfolio accounts) and at individual investor perspective using macro-models (aggregate indicators e.g. price indices).

2.4.3.1 Studies in the US market

Using micro-level data, the seminal paper of Lakonishok, Shleifer and Vishny (1992) documents some existence of herd behavior among institutional investors (pension funds). The authors investigate herding among institutional investors, particularly fund managers who manage pension funds. Using their own methodology Lakonishok, Shleifer and Vishny (1992), (henceforth LSV (1992) measure) examine quarterly data over a 5 year period, from 1985 to 1989, covering 769 US tax exempt funds which were managed by 341 fund managers. They find weak evidence of herding among small capitalisation stocks and very little evidence among large capitalization stocks. They also find a weak association between herding in stocks and its past returns. Recent study by Alda and Ferruz (2016) which investigates the relationship between management style and herd behavior among Spanish equity pension funds utilising LSV (1992) measure indicate no evidence of herd behavior.

Grinblatt, Titman and Wermers (1995) investigate the mutual fund market and documents evidence of herd behavior. Using quarterly data for 155 mutual funds in the US market, covering a ten year period from 31 December 1974 to 31 December 1984, they test for herding at stock level using Lakonishok, Shleifer and Vishny (1992) measure. They find that herding was prevalent among growth and income funds. The finding implies that growth funds have limited information regarding their stocks and so investors have an incentive to mimic investment decisions of others. On the other hand, income funds indicate a tendency to hold

large stocks and so institutional investors have a tendency to herd on such a strategy. The authors extended their work by documenting evidence of momentum trading (i.e. tendency to buy stocks based on their past returns) within the fund managers which is related to herd behavior. The study provides insights into why mutual funds profit from their security analysis.

Further research expanded the sample period for the US fund industry. For example, Wermers (1999) investigate herd behavior of all mutual funds over a 20 year- period, from 31 December 1974 to 31 December 1994 and its impact on stock prices. Employing the Lakonishok, Shleifer and Vishny (1992) measure, the study finds weak herding among average stocks and evidence in support of herd behavior among small firms. The study finds a tendency to herd when purchasing stocks than when selling them. Furthermore, consistent with the study of Grinblatt, Titman and Wermers (1995), Wermers (1999) find strong herding among growth funds. The study finds that at subgroups level of the funds, degree of herding is higher among growth-oriented mutual funds relative to income funds. They explain that this is because growth-oriented funds lack precise information regarding their future earnings potential. Wermers (1999) also find superior performance among stocks bought by mutual funds relative to those sold during the six months subsequent to trades. This is more pronounced among small stocks. The study shows that future returns differences are permanent, a finding which indicates consistency with theoretical explanations that argue that herding by mutual fund managers is motivated by fundamental information.

Further research extended the type of investors. For example, Nofsinger and Sias (1999) investigate the cross- sectional relation between changes in institutional ownership and stocks returns to evaluate the comparative importance of herding by institutional investors trading on the New York stock exchange (NYSE), over the period 1977 to 1996. Using monthly stocks returns, annual market capitalization and annual fraction of shares held by institutional investors for all firms on NYSE excluding closed end funds; real estate investment trusts (REITS); trusts that issue two types of units namely primes and scores; and foreign companies. Their data set comprise of a minimum of 1202 firms in 1987 to a maximum of 1508 firms in 1996 totalling 24 869 firm-years. They deploy their own measure and evaluate herding over interval and by investor groups. They also evaluate the returns of assets held by institutional investors as opposed to returns realized by institutional investors. They document strong positive correlation between changes in institutional ownership and returns measured over the sample period. They explain that the results either indicate that institutional investors engage in positive feedback trading more than individuals or institutional investors herd behavior

influences prices more than herding by individual investors. They further claim that both herding and positive feedback trading play a role in explaining the relationship between changes in institutional ownership and returns. They show evidence that stocks bought by institutional investors outperform the stocks that they sell indicating their engagement in momentum trading.

Sias, Starks and Titman (2001) investigate the price impact of institutional ownership. They examine the daily, weekly, and quarterly returns of the US market from December 1979 to December 1996. They find evidence that returns are correlated with changes in institutional ownership. The authors explain that this is because institutional trading is largely informed, and influences prices permanently. Their findings are consistent with the studies such as Wermers (1999) and Nofsinger and Sias (1999) supporting informational cascade explanation of herding.

Sias (2004) investigate institutional ownership data in the US during the period March 1983 to December 1997 covering a total of 60 quarters. Specifically, the study analyzes the cross-sectional correlation between institutional demand of a security over adjacent quarters. They also decompose the cross correlation into portions that are attributed to individual institutional investors following own trades and the portions that emanate from institutional investors following other institutional investors trades. Using their own measure, which quantifies the extent to which trades follow each other over adjacent quarters they find evidence of strong positive relation between the fraction of institutions buying over adjacent quarters consistent with both institutional herding and institutions following their own lag trades. Upon decomposition of the herd measure, the study finds that following own trades and following the trades of others plays a significant role in explaining the correlation between institutional demand over adjacent quarters.

Sias (2004) also find evidence that institutions engage in momentum trading consistent with Falkenstein (1996) model of characteristic herding. Specifically, the study finds that US institutional investors are attracted to securities with large lag returns. However Sias (2004) explain that the momentum trading does not largely account for herding. Sias (2004) further finds that herding is stronger in small capitalization stocks relative to large capitalized stocks, consistent with models that suggest that herding results from informational cascades (Banerjee 1992), and Bikhchandani, Hirshleifer and Welch (1992). Sias (2004) also finds that as ownership expands and as market liquidity improves, institutional investors are not likely to

follow own lag trades. Finally Sias (2004) documents evidence that various investor types herd differently, for example, they show that similarly classified investors tend to follow each other than differently classified investors. However, the study does not find evidence that institutional herding drives prices away from their fundamental values indicating that there is no evidence of price destabilization.

Recent studies have further documented evidence of herd behavior in the US, such as Gutierrez and Kelley (2007), Lin and Swanson (2008), Puckett and Yan (2008), Yan and Zhang (2009), Choi and Sias (2009), and Liao, Huang and Wu (2011). For example, Gutierrez and Kelley (2007) investigate the impact of herding effects in the US market. They examine 4115 institutional stock holdings over a period from 1980 to 2005. Using the methodology of Lakonishok, Shleifer and Vishny (1992), the authors find that institutional herding generally leads to destabilization of prices, similar to the findings of Puckett and Yan (2008) and Brown, Wei and Wermers (2014). The authors also find that relationship between institutional herding and price reversal is caused by herding generated by buyers. They state that buyers drive asset prices above their fundamental values while sellers move prices towards the correct levels. They explain that this is due to lack of information by those buying while the sellers are better informed. They also explain their findings using the theory of De Long *et al.* (1990) which states that the smart managers may participate in the destabilization instead of correcting prices because the less informed make it optimal for exploitation of profit opportunities than trading against the tide.

Lin and Swanson (2008) investigate herd behavior and investment performance of foreign investors in the US during the period 1990 to 2003. The study deploys LSV (1992) measure and Sias (2004) methodology to test for herding. They find weak evidence that foreigners collectively trade in the US market within 30 calendar days. Using Sias (2004) approach, they find significant evidence that foreign investors (countries) tend to follow each other into and out of the US market over adjacent periods.

Puckett and Yan (2008) examine 776 institutional investors in the US over the period 1999 to 2004. Using the measures of Lakonishok, Shleifer and Vishny (1992) and Sias (2004) the authors document strong evidence of institutional herding at weekly frequency. They further find that institutional herding has important implications for asset prices. Specifically, they document evidence of return reversals following institutional selling and price continuation following institutional buying. They state that herding destabilizes prices contrary to the

finding of Nofsinger and Sias (1999), Wermers (1999) and Sias (2004). They explain that the return reversals are generated by non-informational herding. Their results are consistent with the hypothesis that herding that arises from buying is largely rational while that which results from selling is motivated by liquidity or other behavioral concerns. Using the Sias (2004) methodology, the authors find strong evidence of temporal dependence in institutional trading which is motivated by institutions following their own trades and the trades of others. They explain that institutions exert price pressure when they sell, driving prices below their fundamentals while buying pressure drives prices above their intrinsic values. They observe that buying pressure is often information based while selling is driven by behavioral biases.

Yan and Zhang (2009) investigate the US stock market. Using quarterly institutional holdings from 1980 to 2003, the authors examine whether institutions have preference for stock characteristics and the degree to which their investment horizon influences the relationship between institutions' ownership and future stock returns. They find strong relationship between institutions' investment horizons and their informational role. Specifically, they find that short-term institutional investors (active traders) influence the positive relationship between institutions' ownership and future stock returns, consistent with the hypothesis that short-term institutions are better informed than long term institutions. The implication of the study is that it contradicts a widely held view in literature that long-term institutional investors are beneficial for firms in the long run. Choi and Sias (2009) investigate industry herding in the US market under rising and falling markets as well as industry level from 1983 to 2005. Using various models they document overwhelming evidence of industry herding averaging at 0.4. For example, using the model of Dasgupta, Prat and Verardo (2011a) approach they find that institutional investors follow each other into and out of the same industries which results from managers' decision other than underlying investors' flows. Using the Barberis and Shleifer (2003) model of style investing which tests whether institutional investors' preference for industries with high lag returns might drive their herding, the authors find that momentum trading does not explain their herding. The authors suggest that institution investors engage in momentum trading because the institutional investors actually herd, and their lag demand is positively correlated with lag returns. By deploying the Sias (2004) model, they document mixed findings for reputational herding. For example, they find that four out of five investor groups are more likely to follow similar investor groups than differently classified investor groups consistent with reputational herding explanation. However, they find weak evidence that mutual funds and independent advisers who should be more concerned about their

reputation herd more than other institutional investors which appears inconsistent with the theory of reputational herding.

Choi and Sias (2009) also find that when institutional investors have electronic access to other investor's positions, there is a minor increase in herding. However, the authors observe that there is a small increase in herding following mandatory electronic filing consistent with correlated signals theory. The implication of the results suggest that drivers of institutional herding have an industry component. For example, institutional investors may herd due to reputation concerns by adjusting industry positions as well as stock positions. The same may apply to fads, information cascades and investigative herding. Choi and Sias (2009) also demonstrate that style investing requires a group of investors to herd a style and that such herding influences prices. This shows that institutions tend to herd to industry styles consistent with the hypothesis that herding impacts prices. The results of Choi and Sias (2009) are largely consistent with investigative herding explanation i.e. the models of Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam and Titman (1994) which argue that correlated signals drive herd behavior among institutional investors.

Liao, Huang and Wu (2011) examine the role of investor sentiment in mutual fund herding in the US market. Using the period January 2001 through December 2005 and analysing the mutual fund stock holdings, they find a positive relation between the measure of sentiment and subsequent sell herding. The result indicates that institutional herding may be explained by investor sentiment. They do not find evidence of significant correlation between the sentiment measure and subsequent herding on the buy side.

Brown, Wei and Wermers (2014) investigate the association between institutional trading and analyst recommendation revisions. They document evidence of mutual fund herding in the US dating from 1985 to 2008. Deploying the metric developed by Lakonishok, Shleifer and Vishny (1992), they find that mutual fund managers follow analyst's recommendation by buying stocks when analysts recommend an upgrade and selling stocks for downgrade recommendations. The authors also document asymmetrical reaction to the recommendation, where managers react more strongly to downgrades than upgrades due to fears of reputational damage and risk of litigation. Brown, Wei and Wermers (2014) further investigate price impact of institutional herding and observe that institutional herding elicited by revised analyst recommendations potentially leads to price destabilization. They explain that this price impact is motivated by non-fundamental information. Specifically, they find that fund managers who are concerned

with career issues in the short run overreact to analyst revision leading to price reversals. This finding is consistent with Dasgupta, Prat and Verardo (2011b) theoretical prediction that reputational concerns by fund managers may influence their trading to overreact in the short term and reverse in the long term.

Celiker, Chowdhury and Sonaer (2015) investigate mutual fund herding and its influence on stock prices in the US. Their sample comprise of all funds in the Thomson-Reuters Mutual Fund Holdings database during the period 1980 to 2013 excluding all international funds and non-equity funds. They deploy Lakonishok, Shleifer and Vishny (1992) and Sias (2004) methodologies. Using LSV (1992) measure they find strong evidence of herd by mutual funds consistent with study of Choi and Sias (2009). They also find strong evidence of herd behavior by mutual funds using Sias (2004) measure. Their findings show that herd behavior by mutual funds is not price destabilizing in contrast with the study of Gutierrez and Kelley (2007) and Dasgupta, Prat and Verardo (2011a, 2011b).

Additional literature documents empirical evidence from analyst's recommendations. For example Guo, Holmes and Altanlar (2020) investigate the impact of revised analyst recommendations and sentiments on institutional trading behavior in the US market. Deploying the Sias (2004) methodology on institutional holdings data from December 1993 to December 2015, they find strong evidence that analyst recommendations and sentiments separately and jointly influence institutional herd behavior. This means that institutional investors utilise information from the analysts' recommendations. This suggests that institutional herding results from extracting similar information from analysts' recommendations, hence investigative herding and so the herding does not result from following other institutional trades.

2.4.3.1.1 Summary of studies in the US

From the foregoing macro-level studies in the US market, it can be observed that there is a consensus about the existence of herding. However, there is disagreement over the price impact of herding behavior. For example, a body of studies such as Lakonishok, Shleifer and Vishny (1992); Grinblatt, Titman and Wermers (1995); Nofsinger and Sias (1999), Wermers (1999), Sias (2004), and Choi and Sias (2009) claim that herding is price stabilizing. On the other hand, studies such Gutierrez and Kelley (2007), Puckett and Yan (2008) and Dasgupta, Prat and

Verardo (2011a, b) and Brown, Wei and Wermers (2014) claim that herd behavior is price destabilizing. This suggests an open question on price impacts of herd behavior.

2.4.3.2 Micro level studies outside the US

From examining micro-level studies within the US, we move to micro-level studies outside the US market that investigate herd behavior. For example Choe, Kho and Stulz (1999) investigate the trading influence of foreigners in Korea during the Asian crisis. Using the LSV (1992) measure, they report that that foreign investors exhibit herd behavior before the crisis, but they do not find evidence of herding during the crisis. Voronkova and Bohl (2005) investigate herd behavior among pension fund managers in Poland from 1999 to 2002 using LSV (1992) measure. The authors group stocks by size, past performance and industry. They document evidence of strong herd behavior in small stocks and particular industries. Wylie (2005) documents herd behavior amongst UK pension fund managers for the period 1986 to 1993 using semi-annual data. The study utilises the LSV (1992) measure and finds significant level of herding among fund managers in the largest and smallest stocks which is equivalent to that reported in the US market. Kim and Nofsinger (2005) investigate institutional herding among members of intra-firm business network in Japan during the period 1975 to 2001 using the methodology of Nofsinger and Sias (1999). They find evidence of herd behavior but report that it is lower than recorded in the US market. They however report that herd behavior highly influences prices in Japan than it does in the US. Their findings suggest that members of the network possess inside information and so are less likely to herd than non-members.

Chen and Hong (2006) examine the influence of analyst earnings announcement on returns by institutional investors in Taiwan during the period 2001 to 2003. Using high frequency data (daily), they find evidence of buy herd behavior among large-capitalized stocks and selling herd behavior among small- capitalized stocks. They also document herd behavior in specific stocks with characteristics such as high beta, high return on equity, high liquidity and volatility. They find that institutional investors are more informed in their buying behavior than in their selling behavior. This suggests that buy herding is motivated by information while sell herd behavior is not informative. Walter and Weber (2006) investigate herd behavior among German mutual fund managers during the period 1998 to 2002. They use LSV (1992) measure. They document strong levels of herd behavior relative to those recorded in the US and UK markets.

Lobao and Serra (2007) investigate herding effects among Portuguese mutual funds from 1998 to 2000. Using the herding measure of Lakonishok, Shleifer and Vishny (1992) which compares proportions of mutual funds that buying or selling stocks in a particular period to another if herding effect was absent, they find strong evidence of herding amongst institutional investors. Specifically, for every 100 Portuguese institutional investors that trade in a particular direction (buy or sell) of a stock, about 11 trades in one direction, beyond expectation, if they were trading independently. The degree of herding is 4 or 5 times larger than one observed in developed market such as the UK or USA indicating higher irrational behavior in volatile Portuguese market compared to developed markets. They also document strong herding amongst medium capitalized stocks relative to large or small capitalized stocks. They claim that herding effect declines during boom or volatile period. Their results are consistent with information based models of Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992), and Lakonishok, Shleifer and Vishny (1992). Lin and Swanson (2008) investigate behavior of foreign investors from emerging and developed countries in the US market during the period 1990 to 2003. The study deploys LSV (1992) measure and Sias (2004) methodology to test for herding. They find weak evidence from foreign investors buying or selling stocks within a month. At country level, however, they find that foreign investors herd into various markets over adjacent periods.

Zhou and Lai (2009) investigate herd behavior in a transparent and purely order driven Hong Kong stock market during the period January 2003 to December 2004. Using the intraday data, deploying a modified LSV (1992) measure, they document that herding is prevalent in small stocks. They also find that investors are likely to herd when selling than when buying stocks. The finding is consistent with literature on information cascades. Their findings suggest that the herd behavior is a result of information cascade regardless of the informationally efficiency nature of the market. Zhou and Li (2009) investigate herd behavior among Chinese institutional investors during the period first quarter of 1999 to second quarter 2005. Deploying the LSV (1992) measure, they document herd behavior among institutional investors. In addition, they also find a tendency to chase rising markets and flee from falling markets among both individuals as well as institutional investors. The results suggest that fund managers deviate from client interests consistent with the principal-agent herding model explanation.

Shyu and Sun (2010) examine daily data in Taiwan during the period January 1999 to December 2004, to investigate institutional trading pattern in different economic states. They utilise a modified methodology of Sias (2004) to measure herding among three types of

institutional investors; namely foreign institutional investors, domestic mutual fund investors and domestic securities dealers. They find evidence of herding behavior among all institutional types, notably prevalent among domestic mutual funds investors. However, they find no evidence of herding when the economy experiences significant events such as a presidential election debacle. They claim that the lack of evidence during economic stress suggests that herding among institutional investors is not irrationally driven. This is strengthened by their finding that there is no evidence of return reversals. In their examination of firms of different sizes, they find evidence of strong herding among small firms. They explain that herding is driven by information cascades, consistent with the findings of Sias (2004). Hung, Lu and Lee (2010) analyze quarterly trading data of mutual funds in Taiwan from December 1995 through December 2006 covering 45 quarters. Using the methodology of Sias (2004), they document evidence of herd behavior. Specifically they find that mutual funds follow their own trades than following other funds trades. They find that the herd behavior is price stabilizing when the herds buy undervalued stocks which suggests that it is motivated by value relevant information. This herd behavior is consistent with the explanation of Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam and Titman (1994). They also document evidence of price reversals following selling behavior which suggests that such tendency destabilizes prices as it is likely driven by non-information consistent with characteristic herding. Chang (2010) analyze the role of a transparency policy and its impact on the trading behavior of institutional investors in Taiwan during the period December 2000 through December 2005. They specifically examine whether the practice of daily disclosure of qualified foreign institutional investors trading to the public influences herding. They find that Taiwanese investors (both domestic institutions and individuals) follow the trading behavior of qualified foreign investors and such behavior tend to lead to high volatility. This is consistent with the findings of Hung, Lu and Lee (2010) . They also document that that the trading in concert of institutions and margin traders implies that the less informed traders provide liquidity in the market and potentially register losses.

Jeon and Moffett (2010) investigate the impact of herd behavior on stock returns in the Korean market. Using the monthly stock returns from 1992 through 2003 and deploying the methodology of Nofsinger and Sias (1999), they document evidence of significant influence of foreign investors' herd behavior on stock returns. They explain that this is due to their larger overall ownership relative to domestic institutional investors. They also find evidence of positive feedback trading by foreign investors. They however do not find any evidence that

domestic institutional investors have a strong influence on stock returns consistent with the hypothesis that the impact of domestic institutional investors on emerging markets is weaker relative to foreign institutional investors.

Holmes, Kallinterakis and Ferreira (2013) analyze monthly holdings of individual funds in the Portuguese stock market between January 1998 to December 2005. They investigate herding under various market conditions. Using the methodology of Sias (2004), they document evidence of herding. They find that herding is prominent during the periods when the market returns are low and in post crisis period. They argue that their results are consistent with intentional herding. They explain that given the concentrated nature of the market relative to developed markets, the managers have knowledge about the behavior and strengths of the other managers and so intentionally follow others. Lu, Shen and Fang (2013) investigate herd behavior among bank's lending activities in Taiwan between 2002 and 2011. They deploy Sias (2004) measure and find that generally banks follow own loan patterns and other banks loaning tendencies in industrial lending. They explain that the herd behavior is largely investigative rather than informative. They also find that herd behavior does not vary in market conditions, although there is significant herding during bullish condition for middle and large capitalisation industries for all lending activities. They explain that banks do not supervise borrowers and choose to ride with the tide. More generally, herding among banks in Taiwan is driven by the competitive environment in which banks operate. This is consistent with reputational herding.

Gavriilidis, Kallinterakis and Ferreira (2013a) investigate intentional industry herding, and association between presence of intent in industry herding and specific conditions of each industry or entire market conditions. Specifically, they test whether institutional industry herding is intentional or spurious for the entire Spanish market as well as specific industry sectors. Using quarterly portfolio holdings of mutual funds and applying the methodology of Sias (2004) for the period June 1995 to September 2008, they document evidence that Spanish institutional investors have a strong tendency to herd at the market level. They also find support for significant herd behavior for specific sectors when such sectors register negative market returns, high volatility or high trade volumes. They explain that such herding is intentional and is due to informational and reputational concerns. This is consistent with the theoretical explanation by Scharfstein and Stein (1990).

In another study, Gavriilidis, Kallinterakis and Ferreira (2013b) investigate the effect of style-investing¹⁸ over institutional herding in Portugal during the period July 1996 through June 2011. They analyze monthly portfolio holdings data for 65 equity funds. They deploy Sias (2004) model to assess the temporal dependence of institutional demand. The results of their analysis show a high magnitude of monthly cross-sectional correlation of institutional demand suggesting that Portuguese equity fund managers exhibit a strong temporal dependence. They explain that the temporal dependence emanates from institutional herding, however style investing is not fully responsible for the herd behavior. The authors further extend their analysis to examine the influence of style investing over herding following Portugal's entry into the EURONEXT¹⁹. They find that following the merger, factors such as transparency and improved quality of information, style investing influences herd behavior.

Choi and Skiba (2015) investigate institutional herding across international markets. They utilise the methodologies of Sias (2004) and Choi and Sias (2009) to compute herding propensities and test whether herding is price stabilizing; and whether information asymmetry is related to herding propensities. They find strong evidence of widespread institutional herding across countries and that it is driven by fundamental information. Specifically, they find a significant positive relationship between current institutional demand and current quarter returns. They do not find any evidence of price reversals and so claim that herding is an institutional mechanism through which fundamental information is impounded into asset prices. They claim therefore that herding stabilizes asset prices. Choi and Skiba (2015) also find varying herding propensities across countries which is explained by country-specific information asymmetry. They state that herding is prevalent where there are low levels of information asymmetry (i.e. those with high levels of information transparency). Thus they find an inverse relationship between herding propensities and levels of information asymmetry. Their results are not consistent with the findings of studies which argue that herding is prevalent in areas of high information asymmetry, enabling an environment where investors infer information from trades of others. The authors finding suggests that herding in international market is based on fundamental information about securities and markets which institutions discover independently of each other, consistent with investigative herding theory. Choi and Skiba (2015) also find that herding increases the speed of adjusting of information to drive prices towards fundamentals in markets that are informationally transparent. Specifically, they

¹⁸ A form of characteristic trading where investors trade in stocks selected based on specific characteristics such as past returns or its market capitalisation.

¹⁹ It is the pan-European stock exchange and market infrastructure which connects European economies to global capital markets.

find a positive relation between institution demand and concurrent returns to securities in most of the countries. The results of Choi and Skiba (2015) are consistent with those studies which find positive relation between institutional demand and current returns that area accompanied by lack of price reversals such as Nofsinger and Sias (1999), Sias (2004), Puckett and Yan (2008) and Choi and Sias (2009).

Economou, Gavriilidis, Kallinterakis and Yordanov (2015) investigate herd behavior among fund managers in Bulgaria and Montenegro during the period January 2005 to December 2012. They evaluate quarterly data from 25 funds in Bulgaria which trade in 143 stocks while in Montenegro, they cover 6 funds trading in 82 stocks. Using the methodology of Sias (2004), they document presence of strong herd behavior among fund managers in both markets. Specifically, Economou *et al.* (2015) find that in both markets, fund managers significantly herd during quarters of up-markets and high volume. In Montenegro, they find that herd behavior is also significant during periods of low volatility. The authors argue that their findings are consistent with models that document intentional herding in anticipation of information payoff such as Devenow and Welch (1996) and Bikhchandani, Hirshleifer and Welch (1992); and professional payoffs (Scharfstein and Stein 1990). They argue that herd behavior in rising market is either due to less-abled fund managers mimicking trades of relatively more-abled fund managers to avoid underperformance or to collective exploitation by fund managers of irrational traders during rising market periods. They also explain that herding during periods of high volume is due to such high-volume effect in reducing frictions in trading which encourages abled managers to trade in their information, hence facilitating their monitoring on behalf of the less- abled managers.

Alda and Ferruz (2016) deploy the Lakonishok, Shleifer and Vishny (1992) measure to test the relationship between herd behavior and investment strategies among Spanish equity pension funds. They analyze monthly returns for the period January 1999 to September 2012. They find weak evidence of herd behavior in general and little performance related herding. Their results are consistent with the study of Lakonishok, Shleifer and Vishny (1992). They explain that lack of evident herding is due to deployment of distinctive trading strategies by pension fund in pursuit of high performance which is not only risky but also not highly rewarding.

Fang, Lu, Yau and Lee (2017) document existence and impact of institutional herding in Taiwan stock market. They deploy the methodology of Sias (2004). They focus on examining varying market periods to examine herding. The authors find that generally foreign institutional

investors significantly follow their own trades and trades of others, but they do not find evidence of cascading behavior in contrast to the findings of Sias (2004). They also find that momentum trading does not account for herding in Taiwan. They document that foreign institutional investors follow own lag trades for stocks from large- capitalised companies consistent with the hypothesis that institutional investors follow themselves due to trading costs. They state that foreign institutional investors herd in large-capitalised stocks due to following large-capitalised benchmark consistent with investigative explanation. The study argues that foreign institutional investors exhibit rational herd behavior. Fang *et al.* (2017) also find that there is no variation in information cascades emanating from during bullish or bearing periods. However, they find significant decline in foreign institutional investors own cascades in the smallest capitalised securities with the most frequent traders by foreign institutional investors in the bullish period. They claim that this explains why foreign institutional investors speedily enter and exit their positions during the period of high market liquidity due to the hypothesis of trading costs by Sias (2004). Fang *et al.* (2017) also show that foreign institutional investors and dealers follow similar type of institutions than different types consistent with Falkenstein (1996), Gompers and Metrick (2001) and Bennett, Sias and Starks (2003) findings that herding is driven by characteristics or reputational concerns. Security dealers' exhibit strongest tendency to herd in relation to the same type institution due to reputation reasons consistent with Sias (2004). This result shows that foreign institutional investors in Taiwan are subject to various theories of herding.

Lu, Fang and Lee (2017) investigate trading behavior of UK fund managers during the period January 2002 to December 2009. Using the methodology of Sias (2004), they find significant herd behavior among fund managers. They explain that the herd behavior is strong in both bullish and bearish periods of the stock market. They also document that herding in large-capitalised stocks is due to information reasons and therefore related to characteristic herding. They also report that growth fund and international funds follow similar funds, and this is due to reputational and characteristic concerns. This suggests that the herding by growth and international funds is due to non-informational reasons.

2.4.3.2.1 Summary of micro level studies

The foregoing empirical studies that utilise micro level data provide captivating findings about institutional investor trading behavior. First, it is clear in literature that herd behavior is

prevalent among both large and small sized firms. The large firms are often prioritized in respect of research coverage and as such there is readily available information about the firms. In addition regulatory requirements in emerging countries require that institutional investors place funds in secure stocks. For example, the study of Voronkova and Bohl (2005) indicates that Polish pension fund managers earn a minimum rate of return which compels institutional investors to invest in large capitalised firms. Further, many funds are connected with particular market indices. The performance of funds is often a benchmark of these indices, as such institutional investors often trade in stocks that are linked with the index. It is therefore likely that institutional investors will hold a portfolio of stocks that replicates the benchmark, and it is often from large capitalisation stocks.

Literature suggests that small stocks do not attract research coverage as large stocks. In addition, it is often costly for investors to monitor small stocks. Lack of information and low liquidity on small stocks enable them as targeted candidates for speculation. Wermers (1999) findings suggest that institutional investors are likely to ignore their own information and follow the herd when dealing in small stocks.

Various studies show that herd behavior is significantly higher in emerging countries relative to developed countries due to information asymmetries. Institutional investors do not rely on information in such economies due to credibility issues as such tend to herd. Studies such as Holmes, Kallinterakis and Ferreira (2013) show that concentrated markets register higher levels of herding while studies such as Gavriilidis, Kallinterakis and Ferreira (2013a) and Lu, Shen and Fang (2013) indicate that lack of information drives intentional herding consistent with literature on reputational and characteristic concerns.

It is also suggested in literature that institutional herding is not price destabilizing, particularly for developed markets. For example, studies such as Nofsinger and Sias (1999), Sias (2004), Puckett and Yan (2008), Choi and Sias (2009), Dasgupta, Prat and Verardo (2011b), Choi and Skiba (2015) and Celiker, Chowdhury and Sonaer (2015) suggest that correlated signals among institutional investors drives herding relative to emerging markets. Thus it is investigative herding that characterises developed countries (Guo, Holmes and Altanlar 2020).

2.4.3.3 Macro models studies

Another strand in empirical studies employs aggregate market data to investigate herd behavior. These studies deploy the return based methodologies (Christie and Huang (1995), Chang,

Cheng and Khorana (2000) or factor sensitivity (beta) dispersion methodology (Hwang and Salmon 2004).

Christie and Huang (1995) introduced a methodology that examines the cross-section dispersion of stock returns. The method largely uses prices data. The authors analyze daily data of the New York Stock Exchange (hereafter NYSE) firms from the US market during the period July 1962 to December 1988. They also examined monthly returns from January 1926 to December 1988, covering 756 observations. They find that dispersions did not increase significantly during periods of extreme market movement indicating absence of herding. Chang, Cheng and Khorana (2000) modified the methodology of Christie and Huang (1995) to provide for non-linearity by measuring the cross section absolute deviation of returns. They deploy their method by testing for herd behavior in three developed countries namely US (1963-1997), Hong Kong (1981-1995), Japan (1976-1995), and two emerging markets namely South Korea (1978-1995) and Taiwan (1976-1995). They find evidence of herd behavior in emerging markets during periods of extreme positive and extreme negative market conditions, however, find no evidence for the developed markets. Later, Hwang and Salmon (2004) develop their own methodology that considers changes in fundamentals and time series volatility *inter alia*. They test for herding in the US and South Korea during the period 1993 and 2002. They document strong evidence of herd behavior in both markets. They argue that herding is less prevalent during the extreme conditions but more prevalent before and after extreme conditions.

Tan, Chiang, Mason and Nelling (2008) investigate herd behavior in the Chinese market using daily (July 1, 1997, to December 31, 2003), weekly and monthly (January 1, 1996 to December 31, 2003) data. They deploy the method of Chang, Cheng and Khorana (2000) and document significant evidence of herd behavior for both stock exchanges (Shanghai and Shenzhen). Tan *et al.* (2008) find that both domestic individuals (dominate in A-market) and foreign international investors (who dominate in B-market) herd in their respective A-share and B-share markets where they dominate. They find that herding is stronger at daily level and weaker at weekly and monthly level, indicating that herd behavior is a short-term behavior. They also find herd behavior during rising market, and when the trading volume and volatility are high.

Goodfellow, Bohl and Gebka (2009) investigate the presence of herding in the Polish stock market during various economic periods. Using the methodologies of Christie and Huang (1995) and Chang, Cheng and Khorana (2000) they analyze daily prices from July 1996 to

November 2000. They document evidence of stronger herding by individual investors during periods that the market declines relative to period of rising economic activity. The authors explain that this is due to investor sentiment implying confidence in their own beliefs as the market takes a bullish trend. They also document that institutional investors do not herd during both periods indicating that individual investor herding is likely due to being less informed.

Chiang and Zheng (2010) investigate herd behavior in advanced stock markets (Australia, France, Germany, Hong Kong, Japan, UK, and USA), Latin American countries (Argentina, Brazil, Chile and Mexico) and in Asian markets (China, South Korea, Taiwan, Indonesia, Malaysia, Singapore and Thailand). They analyze industrial stock returns covering a number of industries ranging from 53 to 155 during the period May 25, 1988 to April 24, 2009. They deploy their own methodology that builds on the methodology of Chang, Cheng and Khorana (2000). They find evidence of herding activity in all Asian markets and in advanced stock markets excluding the USA. They do not find evidence of herd behavior in Latin American countries. They explain that investors in Asian markets follow global news and take own investment decisions based on those of institutional investors. They explain that the absence of evidence for the US is attributed to a diverse of opinions on investment decisions by various firms and media outlets leading to varying beliefs which generate heterogeneous investors which impairs the likelihood to take collective action. Chiang and Zheng (2010) also analyze data from extreme market environments including the Mexican crisis, Asian crisis of 1997; 1999 Argentinian crisis and the 2008 credit crunch. Using the methodology of Christie and Huang (1995) they find that turbulent periods trigger herd behavior which is contagious and spreads to neighbouring countries.

Demirer, Kutan and Chen (2010) investigate herd behavior at sector level using firm level data in Taiwan during the period January 1995 through December 2006. They analyze daily returns from 689 stocks and apply three methodologies namely Christie and Huang (1995), Chang, Cheng and Khorana (2000) and Hwang and Salmon (2004). They find no evidence of herding using the method of Christie and Huang (1995) except in one sector. However, they report strong evidence of herd behavior across all Taiwanese sectors using methodologies of Chang, Cheng and Khorana (2000) and Hwang and Salmon (2004). The results indicate that compared to the approach by Christie and Huang (1995), the methodologies of Chang, Cheng and Khorana (2000) and Hwang and Salmon (2004) are more reliable in detecting herd behavior due their ability in factoring non linearity.

Fu and Lin (2010) investigate herd behavior among Chinese investors using monthly data during the period January 2004 through June 2009. They deploy the methodologies of Christie and Huang (1995) and Chang, Cheng and Khorana (2000). They do not find any evidence to support presence of herd behavior. However, they find some support for the tendency to herd in low turnover stocks relative to high turnover stock in periods of down-market conditions.

Economou, Kostakis and Philippas (2011) investigate herding effects in Portugal, Italy, Greece, and Spain during the period January 1998 through December 2008. Using the methodology of Chang, Cheng and Khorana (2000), they analyze daily returns for all stocks listed in these four markets and find evidence of herding effects for Greece and Italian markets but none for Spanish market while evidence for Portugal is mixed. They further analyze potential asymmetries with regard to market returns, trading volume and volatility. They report mixed findings. In terms of returns, herding effects in Greece are prominent during rising markets while for Portugal, Spain and Italy, the effect is prevalent during days of negative market returns. With respect to trading volume, the authors document robust evidence that trading volume asymmetrically affect cross sectional dispersion of returns only in Spain i.e. dispersion is reduced on the days when trading volume is high. It is weak for Portugal while Greece and Italy show no asymmetry, indicating that regardless of trading volume, herding effects prevails. Finally, they document potential asymmetric behavior for cross sectional absolute deviations with volatility of market returns for Italy, where herd behavior is most likely to be registered on the days of low volatility while in the case of Greece, volatility does not affect return dispersions.

Gebka and Wohar (2013) investigate international herding by analysing national indices. They deploy two data sets, one covering 32 countries in 5 sectors, during the period 6 January 1998 to 2 January 2005 while another data set covers 27 countries for the period 1 November 2007 to 2 January 2012. They deploy methodologies of Christie and Huang (1995) and Chang, Cheng and Khorana (2000). They do not find herding at the level of market indices. However, when they disaggregate the national indices into specific economic sectors, they document evidence of herd behavior on a global scale. They find that the herd behavior is more pronounced during rising markets and declines over time. Gebka and Wohar (2013) explain that adverse herding is due to localized herding, excessive flight to quality during market stress and overconfidence. The evidence in sectoral stocks is consistent with findings of Zhou and Lai (2009) who analyze transaction level data in Hong Kong and document evidence of herd behavior in information technology stocks. Their results show that during periods of market distress, there is weak

evidence of deviations from the rational return patterns during the financial crisis, in contrast to findings of Chiang and Zheng (2010) who document herd behavior during periods of market stress.

Mobarek, Mollah and Keasey (2014) analyze daily stock returns of European stocks during the period 2001 and 2012. They deploy the measure of Chang, Cheng and Khorana (2000) to capture herd effects. They find that a comparative country-wise analysis does not yield significant evidence of herd behavior during normal times. However they do find significant evidence of herd behavior during market crisis and in regimes of different extreme market conditions consistent with findings of the study of Economou *et al.*, (2011) which documents that herd behavior is more prevalent during the global financial crisis. Yao, Ma and He (2014) examine the tendency to conform towards the market consensus in Chinese stock market covering two stock exchanges. They cover the period 1 January 1999 to December 31, 2008. They deploy the measures of Christie and Huang (1995) and Chang, Cheng and Khorana (2000) to test for herd behavior. The market is segmented into A-shares which are traded by domestic Chinese investors and B-shares which are open to both domestic and foreign investors but denominated in US dollar on Shanghai Stock Exchange and in Hong Kong Dollar on Shenzhen Stock Exchange where foreign institutional investors dominate. They find evidence of significant herd behavior on the B-share market. They also document more pronounced herd behavior across markets at industry level which is stronger for both largest and smallest firms. They find significant herding under conditions of declining markets. They find that herding is also stronger for growth stocks in comparison to value stocks. It however declines over time. They claim that this is due to improvements in information disclosure and market integrity arrangements such as improved corporate governance of listed firms.

Galaritis, Rong and Spyrou (2015) investigate the relationship between release of macroeconomic information and investors trading behavior. They specifically examine correlated trading towards market consensus among top 100 listed companies in the US and UK. They analyze daily prices of all S&P 100 and FTSE 100 stocks during the period October 1989 to April 2011. Using the methodologies of Chang, Cheng and Khorana (2000) and Chiang and Zheng (2010) and after a thorough analysis, their findings show evidence that US investors exhibit correlated trading behavior following the release of fundamental macroeconomic information. This implies that the publication of fundamental information prompts herd behavior, consistent with the literature that such information is likely relevant to the valuation of asset prices. They also find weak evidence of herd behavior being driven by fundamental

information for the UK investors consistent with study of Wylie (2005). The findings of Galariotis, Rong and Spyrou (2015) imply that herd behavior may be driven by factors such as period and geographical location.

Vieira and Pereira (2015) investigate the Portuguese market from 2003 to 2011, using market level data. They deploy two methodologies namely, Patterson and Sharma (2006) which is derived from the model of Bikhchandani, Hirshleifer and Welch (1992) on information cascades; and Christie and Huang (1995) and Chang, Cheng and Khorana (2000) to measure herding. Using Patterson and Sharma (2006) methodology, they find evidence of herding suggesting contradiction of efficient market hypothesis while using Christie and Huang (1995) and Chang, Cheng and Khorana (2000) they do not find supporting evidence for herding. They argue that the results mean that the Portuguese market is likely efficient. They conclude that measure of herding is sensitive to methodology and so argue for review of measurement approaches.

Galariotis, Krokida and Spyrou (2016) examine the role of liquidity of equity stocks on herd behavior among top five international markets namely: US, Japan, Germany, UK and France. They employ the methodology of Chang, Cheng and Khorana (2000) to examine price data from January 2000 to January 2015. They document strong evidence of herd behavior for high liquidity stocks among all countries and during crisis periods except for Germany. They explain that return clustering influences the variance of average equity stock market liquidity especially during the crisis period and after the crisis. They find that this is stronger in the US market relative to other countries. Specifically, they find that approximately 30 percent of the variance in average stock market liquidity is a result of return clustering. This is due to variations in levels of regulation amongst these countries. Vo and Phan (2017) investigate extent and presence of herd behavior in the Vietnamese stock market covering the period January 2005 to April 2015. Using the methodologies of Christie and Huang (1995) and Chang, Cheng and Khorana (2000), they document evidence of herd behavior amongst investors in Vietnam. Their results show that herding is stronger during periods when the market is down. They explain that this is due to investors actions to flee for safety during the period. They also document evidence of herd behavior during high and low volume trading periods with more pronouncement during low volume trade. They do not find evidence of herd behavior during the period of global financial crisis.

Guney, Kallinterakis and Komba (2017) investigate herding in eight African frontier markets during the period January 2002 through July 2015. Using daily data, they deploy the models of Chang, Cheng and Khorana (2000) and Chiang and Zheng (2010) to test for herd behavior. They find evidence of herding across all eight African countries. They explain that this is due to low transparency levels which reduces the quality of information hence inducing herd behavior amongst investors i.e. infer information from their peers' trades. They also find that small- capitalised stocks magnify herd behavior due to increased informational uncertainty about them. They also find significant herding regardless of market direction (state of the market or market returns). They however find asymmetric herd behavior with respect to volatility i.e. herd behavior is stronger during the period when volatility is lower. They also report that herd behavior induced domestically by market returns is stronger relative to herd behavior induced by US and South African market returns, indicating that investors in these countries are not very influenced by international factors, consistent with the literature that suggests low integration of frontier markets within the international financial system.

Kabir (2018) investigate daily returns in the US financial market to examine the influence of the financial crisis on herding. They utilise data from January 1, 2003, to 31 December 2012. They deploy the methodology of Chang, Cheng and Khorana (2000) and its augmented techniques to detect herd behavior. They report evidence of spurious herding during extreme market conditions, specifically during global financial crisis. They claim that spurious herding increases with conditional volatility of returns. In their study, they distinguish between herding due to fundamental and non-fundamental information. They report that investors do not herd during low volatility periods in reaction to fundamental information. They find that generally, there is less frequent intentional herding compared to spurious herding among investors in high volatility regimes suggesting limited spill-over effects of herding when investors face non-fundamental information.

Cui, Gebka and Kallinterakis (2019) investigate herd behavior among investors in closed-end funds in the US market during the period 2 January 1992 through 30 December 2016. They utilise Chang, Cheng and Khorana (2000) and analyze 698 closed-end funds. They find significant evidence of herding which is largely driven by non- fundamental information/noise. They also find that herding is motivated by trading at a discount which increases as discounts grow deeper. They also find that herd behavior is more pronounced in periods of uncertainty than in pre-crisis period.

Komba (2020) analyze actively traded sectors namely industrial and allied; and banking, finance and investment on the Tanzania stock market during the period January 2000 to July 2019. Using daily closing prices and market capitalization data, the study deploys Chang, Cheng and Khorana (2000) model. Komba (2020) finds support for herd behavior in the sectors comprising banking, finance and investment companies. The findings are robust with large capitalisation stocks. Komba (2020) explain that herd behavior could be due to familiarity with the examined stocks and alternatively due to spurious herding. This means prices on the stock market may not reflect their true underlying values. Dalgıç, Ekinçi and Ersan (2021) explore herd behavior in Turkish market using daily and intraday trade data of liquid stocks for different investor types during the period June 3, 2013 to 30 May 2014. They deploy a modified version of Christie and Huang (1995) to consider trading volume instead of stock returns. Their empirical findings show that retail investors demonstrate collective trading behavior largely on large capitalisation stocks while professional investors herd on small stocks. They also find that all types of investor herd in market downturns. Their results are consistent with studies of Sias (2004), Choi and Sias (2009) and Shyu and Sun (2010).

Gavriilidis and Kallinterakis (2021) document empirical evidence of herding behavior in Russia. Using a comprehensive period from 1865 to 1914, a period characterised by imperialism, they deploy the methodology of Chang, Cheng and Khorana (2000) which estimates the relationship between the cross-sectional dispersion of equity returns and the absolute performance of the market. Specifically, they document evidence that herding varies among industries. They also find that herding behavior is more prevalent when the market registers negative performance and during periods of declining volatility. They explain that this is due to rudimentary regulation. This inhibits informational transparency and increases informational ambiguity. They explain that the dominance of speculative individual investors contributes to herding as they are known to rely on signals from trades of others. The growth in herding during declining market contrasts the finding of Lobao and Serra (2007).

From the foregoing, it is clear in literature that several studies have examined developed and emerging countries equity markets. Recent studies focus on investigating herd behavior in cryptocurrency markets. For example, da Gama-Silva, Klotzle, Pinto and Gomes (2019) examine herd behavior and contagion using daily data between March 2015 and November 2015 in the cryptocurrency market. They utilise the modified version of Christie and Huang (1995), Chang, Cheng and Khorana (2000) and Hwang and Salmon (2004) to examine 50 digital currencies selected based on liquidity, market capitalization and data availability to

document evidence of herd behavior. Vidal-Tomas, Ibanez and Farinos (2019) examine herd behavior in cryptocurrency market using the methodologies of Christie and Huang (1995) and Chang, Cheng and Khorana (2000) during January 2015 and December 2017. They investigate 65 cryptocurrencies and document extreme dispersion of returns during declining market conditions indicating inefficiency and the risk of cryptocurrency. Kallinterakis and Wang (2019) utilise the methodology of Chang, Cheng and Khorana (2000) to document significant herd behavior in the cryptocurrency market during the period December 2013 to July 2018. They find that strong herd behavior during up market, low volatility and high-volume days. They claim that herd behavior is potentially destabilizing in this market. Ballis and Drakos (2020) utilise the approach of Chang, Cheng and Khorana (2000) to analyze daily data of 6 major cryptocurrencies during the period August 2015 to December 2018. They document evidence that investors act irrationally by imitating other investors decisions without any information.

Youssef (2022) investigates herd behavior using the model of Chang, Cheng and Khorana (2000) and time-varying approach. The results are mixed. Using the model of Chang, Cheng and Khorana (2000), the study reports significant evidence of anti-herding while the time-varying approach reveals that investor behavior varies with time. The study reports that the level of herding increases with volatility, the S&P 500 and the dollar index suggesting that investors interpret rise in volatility, the S&P 500 and the dollar index as negative news and so investors cushion themselves by following the consensus.

These studies suggest varying market conditions under which herd behavior in cryptocurrency market is documented.

2.4.3.3.1 Summary of macro-level studies

The empirical findings from studies that utilises aggregate level data show pertinent macro issues. For example, the studies show that investors do not exhibit herd behavior during period of market stress. The herding measure by Christie and Huang (1995) is designed to detect herding during periods of market stress. On the other hand, Hwang and Salmon (2004) measure captures both periods of market stress and normal periods. The argument is that investors are reluctant to herd during periods of market stress as high volatility that reigns impede market direction. Hence volatility reigns during periods of market stress. This possibly explains why many studies do not detect herd behavior during periods of market stress.

It is also evident from literature that approaches such as Chang, Cheng and Khorana (2000) and Hwang and Salmon (2004) that provide for non-linearities between the dispersion of returns and the market returns successfully detect herding than models that assume linearity such as Christie and Huang (1995). Literature suggests that non-linearities are due to market microstructure explanations such as short sale constraints, information disclosures, overreaction and underreaction to new information and how market prices are corrected. It is also likely that market imperfections such as high transactions costs explain why investors may be reluctant to trade leading to failures in incorporating information into market prices. Non-linearities may also be due to lack of synchrony between the frequency of information that is pertinent for pricing e.g. earnings announcement and the frequency of prices. The fact that existence of herding is detected by one measure (e.g. Chang, Cheng and Khorana (2000)) but not by another e.g. Christie and Huang (1995) suggests that the assumptions about linearity do not hold as asserted by Demirer, Kutan and Chen (2010) and may indicate that the linear models are not efficient. The empirical results in the foregoing studies have demonstrated that studies that utilise non-linear models are precise in detecting herd behavior than linear models.

Herding is sensitive to market conditions as reported in the studies such as Chang, Cheng and Khorana (2000), Chiang and Zheng (2010), and Holmes, Kallinterakis and Ferreira (2013). However, the empirical studies such as Zhou and Lai (2009), Choi and Sias (2009) Shyu and Sun (2010), Holmes, Kallinterakis and Ferreira (2013), Gavriilidis, Kallinterakis and Ferreira (2013a) and Dalgiç, Ekinici and Ersan (2021) have shown that herding trends become more significant during down markets. Economou, Kostakis and Philippas (2011) document that herd behavior is more prevalent during the global financial crisis. Guney, Kallinterakis and Komba (2017) attribute this development to investors risk aversion. If investors face the potential for losses during down markets, they are likely to herd on the sell side to quickly exit the market and cut losses. The findings of Galariotis, Rong and Spyrou (2015) imply that herd behavior may be driven by factors such as period and geographical location. Further, herding itself may be sensitive to type of financial market. For example, the study of Philippas *et al.* (2013) documents herding in the US stock market but not in the US real estate market.

Overall, while herding is prevalent all over, it appears to be less prevalent in developed markets compared to emerging markets and frontier markets. In developed markets, the macro-level studies identify herding during financial turbulence/down markets and driven by fundamental information, for example Philippas *et al.* (2013), Galariotis, Krokida and Spyrou (2016) and Zheng, and Li and Chiang (2017).

2.4.3.4 Other methodologies

Methodologically different from utilisation of micro and aggregate level data, literature also provides other methods of detecting herd behavior such as Frey, Herbst and Walter (2014), Chiang *et al.* (2013) and Zheng, and Li and Chiang (2017). For example, Frey, Herbst and Walter (2014) investigate herd behavior of German mutual fund investors during the period 1998 to 2004. In comparison to the traditional measures of herding estimates, particularly the Lakonishok, Shleifer and Vishny (1992) measure, the authors utilise their own measure and find higher levels of herd behavior than depicted by those of the former measure. They also find higher levels of herd behavior amongst smaller stocks compared to below average estimates given by traditional measure. Finally, they find higher levels of herd behavior during crisis period than those depicted by tradition measure. They argue that their method provides higher statistical properties which may aid researchers to discern patterns that may not be detected by traditional methods.

In another study, Humayun Kabir and Shakur (2018) investigate herd behavior in south Asian (China, Hong Kong, India, Korea, Malaysia, Singapore, Taiwan and Thailand) and Latin America countries (Argentina, Brazil, Chile and Mexico). They use stock markets' daily returns of all firms of each country including dead stocks over the period January 1995 to December 2014. The researchers deploy various methodologies including Chang, Cheng and Khorana (2000) and Chiang *et al.* (2013) an augmented model based on Kalman filtering model. The methodology of Chiang *et al.* (2013) suggests that herding is positively related to state of market returns while negatively related to market volatility. They argue therefore that in order to disentangle the nonlinearity where both market return and volatility exhibit substantial variation with regime switches (up or down market), they utilise smooth transition regression (STR hereafter) model to investigate herd behavior. They find contrasting results for using different methodologies. For example, using Chiang *et al.* (2013), they find that generally all the markets herd towards market consensus but the methodology does not detect adverse herd behavior while using the STR method, markets such as China, India, Malaysia, Singapore, Argentina and Brazil do not show nonlinearity in low and high market regimes. They generally find evidence of herd behavior in the countries studied with exception of Argentina and Brazil where evidence of herding is detected in high volatility period. Countries such as China, Hong Kong, Malaysia, Korea and India show significantly strong herd behavior. They claim that during period of extreme market conditions, high volatility influences herding in contrast to

low returns. The findings of Humayun Kabir and Shakur (2018) are consistent with the studies such as Chiang and Zheng (2010) and Chiang *et al.* (2013).

The identified methodologies suggest that findings regarding presence of herding continue to be mixed in research and so there is no definite methodology in place. Vieira and Pereira (2015) conclude that measures of herding are sensitive to methodology and so argue for review of measurement approaches.

Finally, the empirical studies document significant evidence of herd behavior in both developed and emerging markets. The implications of this behavior include price destabilization, excess volatility and systemic risk. The debate in literature shows that the behavior may be driven by both informational and non-information sources. However, there is lack of evidence for less developed countries in literature such as Malawi.

2.4.3.5 Empirical studies on anti-herding

A thread of literature on herding behavior focuses on explaining the findings that show investors acting against the trend i.e. termed anti-herding. Anti-herding has been defined by Levy (2004) as a scenario where decision maker goes against the prior even if they believe the prior to be correct. The author states that the behavior signals decision maker's ability and so there is an excessive incentive to go against the herd. Jiang and Verardo (2018) develop a dynamic measure of fund level herding. They examine USA fund stocks from 1990 to 2009 to document a negative relationship between herd behavior and skill of managers of mutual funds. They claim that while other mutual fund managers herd for reputation reasons, others go against the trend i.e. anti-herd. They explain that difference in ability and information quality drive differences in herding by mutual fund managers. Babalos and Stavroyiannis (2015) document anti-herding behavior in the metals commodities market. They explain that it is driven by different portfolio positioning and rebalancing. Other studies such as Naujoks, Aretz, Kerl and Walter (2009) document anti herd behavior among Germany analyst during the period 1994 to 2005. They find that analysts systematically issue forecasts that vary from the consensus. In addition, Pierdzioch, Rülke and Stadtmann (2013) analyze monthly survey data of price forecasts in the metals market during the period 1995 to 2011 to document forecaster anti-herding. They explain that anti herding behavior is a result of heterogeneity among the forecasters.

The foregoing studies suggest that presence of anti-herding behavior is explained in literature by amongst others decision makers ability, quality of information, portfolio positioning and rebalancing, and heterogeneity of investors.

2.5 Inefficiencies in Least Developed Countries

Empirical evidence that stock markets in emerging markets are manipulated is widely documented. For example, Khwaja and Mian (2005) investigate price manipulation in Pakistan and suggest that price manipulation stems from principal trading. Aggarwal and Wu (2006) posit that manipulation is prevalent in emerging markets. The authors posit that successful manipulative strategy requires collusion amongst players. Khwaja and Mian (2005) study finds that information asymmetry allows a single broker to artificially move prices and make money off other investors which is consistent with theory by Mei, Wu and Zhou, (2005). Several studies such as Aaron, Koesrindartoto and Takashima (2018), Imişiker, Özcan and Taş (2015), Huang and Cheng (2015), Azad, Azmat, Fang, Edirisuriya, (2014), Comerton-Forde and Putniņš (2014) and Imişiker and Taş (2013) document price manipulation in emerging markets. Pirrong (2017) document manipulation in commodity markets. These studies document that the misconduct of some participating market intermediaries and large traders cause harm which creates a risk that can affect market integrity. The evidence challenges efficiency of markets.

Samuels *et al.*, (1981) posits that LDC's do not always have conditions sufficient for an efficient market. Mohtadi and Agarwal (2001) empirically investigate the relationship between stock market development and economic growth. They find a positive relationship using various indicators on economic growth both directly and indirectly. They assert that due to high volatility in LDCs, turnover ratio is a misleading indicator of liquidity in stock markets.

Severino and Baraton (2013) assert that Africa registered a 5 percent annual increase in real Gross Domestic Product (GDP) since 2002; a fivefold increase in foreign direct investment (FDI) between 2002 and 2011; and sharp increases in private equity flows between 2002 and 2008 yet has little to show for its economic development. The authors argue that inefficient allocation of financing is a big impediment to Africa's economic growth in spite of major investment needs, for example in energy and infrastructure. Although there are different views on the significant role of securities markets, there is consensus on the general features of LDCs. *A priori* reasons include: few quoted stocks, limited trades and few investors with little knowledge and in other cases there is inadequate information. Empirical evidence is

documented by studies such as Wai and Patrick (1973), Drake (1977), Singh (1991), and Mohtadi and Agarwal (2001). These studies articulate the following constraints to the development of securities markets: limited number, volume and variety of stocks; thin trading; high volatility; correlation of share price movements; high dependence on external resources to finance fixed investment; weak productive capacity; government dominance in securities markets; low turnover activity; insignificant volume of public float; and substantial role of government in issuance of securities which are largely taken up by a captive market. Drake (1977) further adds that the honesty and capability of brokers is of significance, given that both developed and underdeveloped countries have expressed concerns about their conduct. Wai and Patrick (1973) suggest that stereotypes such as thin trading; poor information and substantial manipulation; and occasional speculative behavior that culminates into a crash are largely a reality. They also argue that historical circumstances, and economic and financial policy contribute to the relatively deleterious role of capital markets.

Svirydzenka (2016) argues that financial development reduces informational asymmetries and financial constraints which enable financial systems to manage and minimize macroeconomic volatility and inequality. In addition, according to the IMF data as of 2021, Malawi's financial markets efficiency index stood at 0 (nil) while that of developed countries such as UK and USA stood at 0.815 and 1 respectively. Further, the Financial Development Index for Malawi stood at 0.095 while that of UK and USA stood at 0.836 and 0.917 respectively. This suggests that LDC's such as Malawi have potential challenges with informational asymmetries which may impact investment decision making.

However, the Malawi Stock Exchange generated an average annual return of 62.4 percent during the year 2013 (return on index from January to December) compared to a return on index of 29.6 percent generated by US Standard and Poor's 500 equity index (Minney 2014). In 2017, it generated an average annual return of 56 percent against a return of 28.2 percent for the NASDAQ, (Minney 2018). This suggests better performance from a least developed country compared to developed countries. It is not known what caused such performance unless empirically tested.

2.6 Financial market structure and Stock Market microstructure in Malawi

2.6.1 Financial market structure

The financial sector is regulated by the Registrar of Financial Institutions who is also the Governor of the Central Bank. It comprises the banking sector, capital markets, pension sector, general and life insurance sector and microfinance institutions sector. Reserve Bank of Malawi (2020) reports that the banking sector includes eight banks, four of which are domestic, privately-owned and comprise of 54.9 percent of total net assets as of end December 2020 while the other four banks are foreign owned and comprise of 44.1 percent of total net assets. “*Ibid.*, 13”, as of end December 2020, total net assets of the banking sector stood at K2.3 trillion (US\$2.9 billion). “*Ibid.*, 16”, the quality of assets deteriorated, as measured by the non-performing loans (NPL) ratio which increased from 6.3 percent in 2019 to 6.4 percent in 2020. However, the banking sector remained adequately capitalized meeting regulatory minimum core and total capital ratios of 10.0 percent and 15.0 percent respectively, registering average core and total capital ratios of 17.7 and 21.4 percent respectively as of end December 2020 (“*ibid.*, 15”). There was a merger of two banks during the year 2020 which resulted into a decline of branch network from 110 branches to 106 branches (“*ibid.*, 12”).

According to the Reserve Bank of Malawi (2020), the pension sector registered growth in assets to close at K1.1 trillion (US\$1.4 billion) by end December 2020 driven by an increase in pension contributions and investment returns. In addition, the membership in pension schemes increased by 9.3 percent to 473 347 (representing 2.47 percent of the population which was at 19.13 million for the year 2020) due to enrollment of new employees under the National Pension scheme (“*ibid.*, 28”). The sector comprised of 29 pension funds of which 19 are stand-alone funds, 2 are self-administered funds and 8 are unrestricted funds (“*ibid.*, 76”). Prior to the enactment of the pension law in 2011, there were numerous self-administered pension funds. The position changed due to the new pension legislation.

The general insurance sector comprised of 8 insurance companies, 24 brokers and 40 insurance agents while the life insurance sector comprised of 6 companies, of which 4 underwrite all classes of life insurance business. Reserve Bank of Malawi (2020) reports that as of end December 2020, the general insurance sector registered improved solvency ratios at 21.6 percent from 18.4 percent in 2019. However, 50 percent of the insurers did not meet the minimum solvency requirement. On the other hand, life insurance sector remained sound and resilient due to growth in assets, gross premiums, decline in net claims and management

expenses compared to the year 2019 with solvency position closing at 165.7 percent, well above the regulatory requirement of 120 percent (“*ibid*”).

The microfinance sector comprised of 4 deposit taking institutions, 11 non-deposit taking institutions, 46 microcredit agencies and 40 financial cooperatives as of end December 2020 (“*ibid.*, 45”). The sector registered 475 204 clients (2.48 percent of population) as of end December 2020 (“*ibid*”). It also registered an increase in assets by 10.7 percent to close at K54.3 billion (US\$69.8 million) by end December 2020 (“*ibid*”). However, it registered losses due to negative effects of the covid-19 pandemic (“*ibid*”).

2.6.2 *Stock market microstructure*

The stock market in Malawi was established in 1994 following reforms under structural adjustment program led by the International Monetary Fund (IMF) (African Markets, 2020). It was being operated by a broker. The initial service was largely secondary trading of government securities namely, local registered stock and treasury bills. The first listing was recorded in November 1996 (“*ibid*”). The Malawi Stock Exchange (MSE) was formally delinked from a brokerage operation and commenced its operations as a company limited by guarantee on 1st April 2000. The market witnessed entry of other brokers who provided competition and price discovery.

As at end December 2020, the exchange had 3 trading platforms (Malawi Stock Exchange, 2024). The first platform styled the main board trades equities from well established companies. There were 16 stocks listed as of end August 2020 (“*ibid*”). The exchange has since its inception registered 2 company restructurings and delisting of 2 companies. It remains the only stock market in Malawi. Due to volatile trading on the listed stock in 2008, several retail investors realized losses due to falling prices of the stock. The effects of the global financial crisis also negatively affected the stock market as prices fell due to massive sell-off amidst capital flight. Private companies stayed away from raising capital on the stock market and opted for bank loans.

The second platform called the alternative capital market caters for small and medium companies. Since its launch in 2008, it has not registered any listings. The third platform caters for listing of debt instruments. It lists both treasury and corporate bonds, totaling 14 as of end December 2019. There are currently 4 stock broking firms. During the sample period, 2 brokers entered the market while another 2 exited the market.

The stockbrokers and the stock exchange are licensed by the Registrar of Financial Institutions. All orders (buy and sell) are executed by the stockbrokers which are members of the exchange. They utilize an automated trading system (ATS) which matches the prices. The market opens from 9.30 hrs to 14.00 hrs from Monday through Friday. Settlement is on T+3 basis. The securities transfers are done in the Central Securities Depositories (CSD) held at the Central Bank while the payments (money transfers) are made through the banking system. Retail trades are prefunded while institutional trades are funded upon production of the contract note by the broker.

As of end December 2020, Reserve Bank of Malawi (2020) reports that other capital market players included 6 fund managers, 2 collective investment schemes, 9 investment advisers and 4 transfer secretaries. The assets under management stood at K1.6 trillion (US\$2.1 billion) as of end December 2020 due to increase in net cash inflows, of which 37.1 percent was invested in equities, 35.0 percent in money markets while the balance was spread across listed debt (0.5 percent), unlisted debt (14.4 percent), unlisted property investments (8.4 percent), unlisted equity (3.3 percent) and other instruments (1.3 percent).

3.0 An examination of the profitability and prevalence of price manipulation by market intermediaries in a least developed country

3.1 Introduction

The misconduct of stockbrokers and price manipulation in capital markets have historically been a concern to academic researchers and policy makers. These matters have a detrimental effect on market efficiency and economic development plans of a country. For example, Guiso, Sapienza and Zingales (2008) document that retail investors shun participating in the stock market if they find it less trusting. Aggarwal and Wu (2006) find that 64 percent of manipulated cases were done by stockbrokers in the USA. Khwaja and Mian (2005) find that principal brokers earn between 50 and 90 percent higher annual returns than outside investors in Pakistan. Imişiker, Özcan and Taş (2015) find that over 50 percent of principal trades conducted were manipulated in Turkish market. Aaron, Koesrindartoto and Takashima (2020) finds that principal brokers earn between 59-92 percent higher annual returns than intermediary brokers in Asian markets.

Understanding manipulation is important. Manipulation impairs the fundamental aspects of market quality, namely, price efficiency and liquidity. Thus, it distorts the accuracy of securities prices and consequently affects liquidity as investors shun the market. Comerton-Forde and Putniņš (2014) posits that price manipulation hurts investor confidence and deters investor participation in stock markets.

Several studies such as Aggarwal and Wu 2006; Comerton-Forde and Putniņš 2011a; Putniņš, 2012; Imişiker and Taş 2013; Huang and Cheng 2015 show that manipulation leads to temporary price impacts, increased volatility, large trading volumes, short-term price continuation and long-term price reversals. Levine, Ross and Zervos (1998) find that stock market liquidity is a robust predictor of real per capita gross domestic product growth and physical capital growth.

This study investigates profitability differentials between principal brokers and outside investors in Malawi, a least developed country (LDC²⁰ hereafter). The aim of the study is twofold. First, emerging markets have witnessed dramatic episodes of market misconduct. For example, Aaron, Koesrindartoto and Takashima (2018), Imişiker, Özcan and Taş (2015), Huang and Cheng (2015), document price manipulation in emerging markets. There are

²⁰ LCDs are classified by the United Nations (UN) based on a combination of geographical and structural criteria which is based on *per capita* income, human asset and economic vulnerability. Malawi remains part of the 47 countries according to 2019 classification

indications that market intermediaries abdicate their role in ensuring price efficiency, speculate by creating feedback trading and eventually distort prices (De Long, Shleifer, Summers and Waldmann 1990). It is timely to consider the nature and level of misconduct in markets that are characteristically different from emerging markets. Second, while there have been studies such as Khwaja and Mian (2005) and Aggarwal and Wu (2006) that have identified manipulation, little attention has been paid to an examination of trading records to establish the problem of manipulative behavior by market intermediaries. We examine that principal brokers engage in unfair trading practice to earn higher returns than outside investors. This has potential to harm price efficiency and economic growth. We thus hypothesize that brokers profitability is positively related to the degree of principalness.

An investigation into the role of market intermediaries in manipulating the stock market is important for LDCs because their inappropriate conduct risks dampening the growth of the stock market as well as attaining economic development plans of a country. As observed in other emerging markets, market intermediaries may resist reforms in order to pursue self-interest and so, their actions may inhibit market development (Khwaja and Mian 2005). The concern is that if least developing countries do not correct inefficiencies to ensure that stock markets facilitate economic growth, then their presence and existence will be cosmetic and of less economic value. In addition, resource allocation will be misaligned and will eventually hurt economic efficiency (Goldstein and Guembel 2008, Comerton-Forde and Putniņš 2014). Therefore, understanding the detrimental effects of behavioral aspects of market intermediaries is significant to policy makers. Pirrong (2017) posit that if regulation does not address market misconduct, investors shift business to markets which provide relatively efficient rules. Consequently, the stock markets will be shunned by individual investors. Policy makers can employ targeted supervisory action to risky areas to effectively detect and correct price manipulation as well as putting in place deterrent enforcement measures. They stand to draw lessons and generate regulations that address behavioral conduct of market intermediaries to ensure they operate efficiently such that asset prices reflect fundamentals. Considering that the context of LDCs has not previously been examined, the findings will provide support to theory why their stock markets remain underdeveloped.

Although studies in behavioral finance have investigated price manipulation by market intermediaries extensively in emerging markets, for example studies such as Aaron, Koesrindartoto and Takashima (2018), Imişiker, Özcan and Taş (2015), Huang and Cheng (2015), Azad, Azmat, Fang, Edirisuriya (2014), Comerton-Forde and Putniņš (2014) and

Imişiker and Taş (2013), there has not been focus on an empirical examination of brokerage accounts for LDCs. Unlike emerging markets which are in transition to greater interaction with international capital markets, LDCs are not, as they characterized differently. Empirical evidence is provided by studies such as Wai and Patrick (1973), Drake (1977) Singh (1991), Mohtadi and Agarwal (2001), United Nations Conference on Trade and Development (2019), which articulate the following constraints to the development of securities markets: limited number, volume and variety of stocks; thin trading; high volatility; correlation of share price movements; high dependence on external resources to finance fixed investment; weak productive capacity; government dominance in securities markets; low turnover activity; and insignificant volume of public float. Further, Drake (1977) adds that the honesty and capability of brokers is of significance given that both developed and underdeveloped countries have expressed concerns about their conduct. In addition, Errunza and Losq (1985) posit that LDCs suffer from insignificant foreign portfolio investments and capital controls. These differences provide a rare chance to examine price distortions in environments that vary from traditional markets. However, Errunza and Losq (1985) further conclude that although LDCs are not as efficient as most developed countries, they are similar to smaller European markets.

According to finance literature, market manipulation techniques contribute to empirical examples on the research area of price destabilizing speculation (Hart and Kreps, 1986; Stein, 1987; DeLong *et al.*, 1990). There have not been studies that focus on an empirical examination of brokerage accounts for LDCs. As such, this study provides potential additional insights into existing manipulative schemes and profitability differentials between market intermediaries and outside investors. The study will focus on examining brokerage trading data, using a unique data set. It is expected that it will enable another contribution by documenting empirical evidence from LDCs. Therefore, this study will build on and contribute to work that depict price manipulation strategies as additional examples of price stabilizing speculation. It will aim to contribute to the growing field that challenges market efficiency by exploring price manipulation (Kindleberger, 1978; Shiller, 1984; DeLong *et al.*, 1990; Allen and Gale, 1992; Shleifer, 2002; Khwaja and Mian, 2005; Mei, Wu and Zhou, 2005; Aggarwal and Wu, 2006; Goldstein and Guembel, 2008).

3.2 Background information

In the previous section, we introduced our study. In this section we describe briefly, details about the stock market under study, features of the data and the methodology to be employed in testing our hypothesis.

The stock market in Malawi was established in 1994 following reforms under structural adjustment program. It was being operated by a broker. The initial service was largely secondary trading of government securities namely, local registered stock and treasury bills. The first listing was recorded in November 1996. The Malawi Stock Exchange (MSE) was formally delinked from a brokerage operation and commenced its operations as a company limited by guarantee on 1st April 2000. The market witnessed entry of other brokers who provided competition and price discovery.

Currently, the exchange has 3 platforms. The first is the main board, which trades equities from well established companies. There are 16 stocks listed as of end August 2020. During the period there has been 2 restructurings and a delisting of 2 companies. It remains the only stock market in Malawi. Between 2008 and 2019, there was no listing. Due to volatile trading on the last listed stock in 2008, several retail investors realized losses due to falling price of the stock. The effects of the global financial crisis also negatively affected the stock market as prices fell due to massive sell off amidst capital flight. Private companies stayed away from raising capital on the stock market and opted for bank loans.

The second is the alternative capital market. It caters for small and medium companies. Since its launch in 2008, it has not registered any listings. The third platform caters for listing of debt. It lists both treasury and corporate bonds, totalling 14 as of end December 2019. There are currently 4 stock broking firms. During the sample period, 2 brokers entered the market while another 2 exited the market. Table 3.1 below shows part of the trading history.

Table 3.1 presents trading information for the stock exchange. It shows that liquidity, measured as percentage of total value traded to market capitalization averaged at 0.19 percent during the period while return on index averaged at 40.42 percent. The exchange has progressed from being a manual trading system with a settlement system of T+7 (trading date + 7days) since inception to operating an electronic central orderbook from 2008. In 2018 the exchange introduced a fully electronic trading system with settlement at T+1.

Table 3.1: Stock Market Trade History from 2004 to 2019

The table presents trading information for the stock exchange namely total value of trades (in million US\$), market capitalization (in million US\$), liquidity measured as percentage of total value of trades to market capitalization and year-on-year return on index.

Period	Exchange rate MWK/US\$	total value of trades in \$ million	market cap in \$ million	Liquidity	Index	Return on index(local currency terms)
2004	108.92	6.01	6842.55	0.09	583.48	
2005	123.78	7.39	9051.21	0.08	906.85	55.42
2006	139.34	7.70	12000.08	0.06	2310.67	154.80
2007	140.30	36.74	12610.28	0.29	4849.79	109.89
2008	140.60	24.17	13078.74	0.18	6091.15	25.60
2009	145.99	19.71	8028.92	0.25	5154.95	(15.37)
2010	150.80	12.35	8478.26	0.15	4953.09	(3.92)
2011	163.75	43.13	16372.50	0.26	5369.42	8.41
2012	337.00	11.79	10570.53	0.11	6015.51	12.03
2013	433.14	30.78	16576.35	0.19	12531.04	108.31
2014	475.82	22.83	15739.87	0.15	14886.12	18.79
2015	668.54	72.68	11251.56	0.65	14562.53	(2.17)
2016	725.43	8.54	11739.99	0.07	13320.51	(8.53)
2017	734.65	18.40	14441.56	0.13	21598.07	62.14

Source: Malawi Stock Exchange. Return on index is own computation from various MSE Annual reports.

Figure 3.1 plots the main index (in log) over the period of the sample from 2007 to 2019. The index data is from DataStream and confirmed by the stock exchange. As indicated earlier, in Section 2.5 the stock exchange generated an average annual return of 62.4 percent during the year 2013 (return on index from January to December) compared to a return on index of 29.6 percent generated by US Standard and Poor's 500 equity index (Minney 2014). In 2017, it generated an average annual return of 56 percent against a return of 28.2 percent for the NASDAQ, (Minney 2018). During the sample period, the stock market experienced rising prices and sparse listings. There was a decade of nil listings between 2008 to 2019. This indicates the limited role of stock market and a common feature of LDCs (Samuels, Yacout and Samuels, 1981, Tafirenyika 2012, United Nations Conference on Trade and Development 2019).

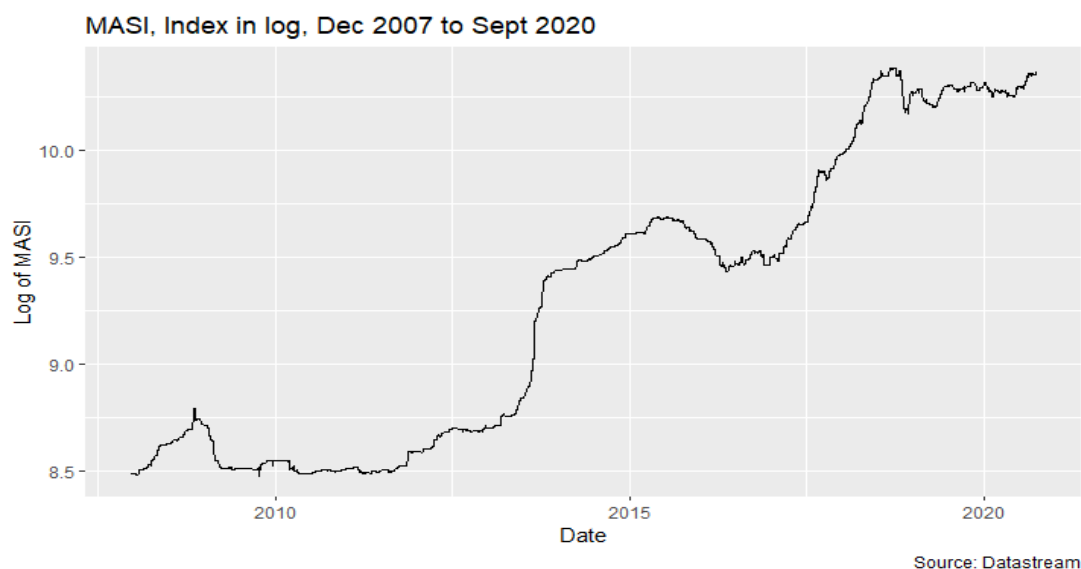


Figure 3.1: Malawi All Share Index in log from 2007 to 2020.

The foregoing depicts features of the market which include rising prices in a shallow market with limited listings and few market intermediaries.

In the previous section, we introduced our study. In the next section we describe briefly, details about the stock market under study, features of the data and the methodology to be employed in testing our hypothesis.

3.3 Data and Methodology

3.3.1 Data

The dataset covers the entire trading history of a least development country stock market, the Malawi Stock Exchange (MSE hereafter) from 11 November 1996 to 18 October 2019. Out of sixteen stocks listed during the period, two delisted. Each trade contains a date stamp, stock code, deal number, transaction price, volume of shares traded, broker identification of whether the trade is a buy or sell. The uniqueness of the dataset is that first, it contains daily trades at individual investor level. This allows direct identification of trades done by brokers either for their own account with those done by outside investors. This contrasts with study of Khwaja and Mian (2005) which utilizes an algorithm to identify principal trades. Second, the volumes of trades are provided at prices at which they were executed. This allows the study the benefit of computing an exact amount of manipulative rent earned by the brokers relative to average prices deployed in the study of Khwaja and Mian (2005). Thus, the study is capable of testing for a specific type of manipulative technique as well as accounting for precise manipulative rents in general. The purpose is to analyze whether brokers engage in trading patterns that earn significantly higher returns than outside investors.

The dataset is obtained from Reserve Bank of Malawi (RBM hereafter), the regulator of capital markets in Malawi. During the study period, there were 4 licensed brokers and 16 stocks. The dataset comprises of 55, 615 transactions. It should be mentioned that the limited number of trades reflect one of the typical features of less developed countries.

3.3.2 Methodology

In the previous section, we described features of our data. In this section, we detail our methodology for measuring price manipulation at the stock exchange and provide evidence for it. Our focus is on brokerage trades. Literature identifies brokers as more likely to engage in price manipulation (Aggarwal and Wu, 2006, Huang and Cheng 2015; Imişiker, Özcan and Taş 2015; Aaron, Koesrindartoto and Takashima 2018). The study of Khwaja and Mian (2005) suggests that brokers generate more profits by trading as principals relative to outside investors. In order to analyze the brokers trading patterns, we examine their trades. We distinguish principal trades which are suspicious trades from intermediary trades. Table 3.2, Description of Trades, show that broker-1 dominates principal trading as well as intermediary trading relative to others. Broker-2 has not registered any trades for other brokers. Broker-3 dominates

trading for other brokers while broker-4 registers the least number of principal trades. In Table 3.2, we present the descriptive picture of trades.

Table 3.2: Description of Trades

Table 3.2 shows that broker-1 dominates principal trading, followed by broker-3. Broker-2 does not trade for other brokers while broker-4 registers the least number of principal trades. Broker 3 moderately trades as a principal while dominates broker to broker trades.

	Broker 1	Broker 2	Broker 3	Broker 4
No of times broker trades for self	347	72	169	6
No of times broker trades for other brokers	139	0	4814	136
Total trades at broker level	30631	9038	14834	518

The uniqueness of our transactional data is that principal trades i.e. those trades that the broker trades for own account are identifiable from intermediary trades i.e. those that the broker trades on account of outsiders. This differentiates our dataset from Khwaja and Mian (2005) study which developed an algorithm to determine the measure of principalness.

3.3.2.1 Type of Principal Trades

In this section we examine the principal trades further. The data are distinguished at stockbroker-ticker-date level. Like in the study of Khwaja and Mian (2005), manipulated trades are categorized into three: principal cycle, principal buy and principal sell. A principal cycle is classified subject to meeting two conditions: first, when the trade is either a buy or sell and is exactly reversed at the next opportune trading session; and second, when the broker buys and sells an exact equal amount of stock (during the same trading day or within 2 days). A principal buy (sell) is when a broker purchases (disposes off) shares in a particular trading session and is not reversed. Intermediary trades are either non-negative and non-equal buy or sell trades. They also do not fulfil the conditions described above. The type of trades are presented in the Table 3.3 below.

Table 3.3: Types of Trades

Each observation is at stockbroker-ticker-date level. A principal cycle is trade that meets the following conditions: either the trade is either a buy or sell and is exactly reversed at the next trading session (1 or 2 days); or the broker buys and sells (or sells and buys) an exact equal amount. Principal buy, if the broker only buys in that trade while Principal sell is when the broker only sells in that trade. A trade is defined as an intermediary if both sale and buy are non-negative and not equal to each other.

Trade Type	Frequency	Percentage by volume		Normalized	Normalized
	Observed (percent)	All but top five	Top five firms	firm price	turnover
	(1)	(2)	(3)	(4)	(5)
Principal Cycle	0.09	0.24	0.22	161.63	27.48
Principal Buy	0.52	0.05	0.39	175.94	18.15
Principal Sale	0.47	0.19	0.38	178.64	24.3
Intermediary	98.93	99.51	99.01	100.0	100.0
Number	56195	23213	32411	55615	55615

Table 3.3 shows that intermediary trades dominate the market at 98.9 percent while the rest are principal trades at around 1 percent (1.08 percent). Column 1 shows three types of trades, principal buys or sales at around half a percent with minimal reversals at 0.09 percent. Column 2 and 3 presents comparative relative frequencies but weighted by traded volume. They show that a significant portion of trades are intermediary trades. Column 3 shows that principal trades occur in the top 5 counters, relative to other counters.

Column 4 shows normalized prices by sample period average in each stock. It is shown that principal sales occur at marginally higher normalized²¹ prices than intermediary trades, although principal buys do not vary widely from the normalized price. It suggests that principal brokers would earn non-negative profit for engaging in principal trading.

²¹ The average prices for each counter for the entire period of the sample, then converted as a percentage.

Column 5 shows that intermediary trades occur at a higher normalized turnover relative to principal trades (normalized by its average in that particular stock over the sample period). Khwaja and Mian (2005) posits that trading at such a low turnover level may suggests liquidity provisioning by brokers. However, principal cycle and principal sales trades occur at a high turnover relative to principal buys.

Due to uneven distribution of stocks traded, we examine volume traded by brokers for top 5 counters. They represent 70.5 percent of total principal trades. It can be noted that while principal trades marginally decline from 1.08 percent to 0.99 percent, respective principal cycles widely increase while principal buys and principal sales marginally decline. We assume the observation is due to the price or declining turnover.

The foregoing investigation shows that principal trading is related to stock prices and trading volumes. The level of principalness is however different from previous studies of Khwaja and Mian (2005), Imişiker, Özcan and Taş (2015) and Aaron, Koesrindartoto and Takashima (2018). These studies find that approximately 50 percent of trades are manipulated.

The next step is to analyze whether such principal trading is systematic for brokers in this market to affect profitability of the market players compared to the rest of the market.

3.3.2.2 Trading Profitability

In the previous section, we described the data and methodology of our study. Our variable of interest is the measure of principalness.

In this section we formalize the measure of principalness, styled PRIN Score, to distinguish suspicious trades from intermediary trades. Khwaja and Mian (2005) develop the PRIN score and interpret it more broadly as the likelihood of a stockbroker to initiate suspicious trades on behalf of either a single investor or a number of investors that act in concert on a specific stock. Such broad interpretation has potential to bias the exact level of systematic trading by brokers. However, the PRIN score is a robust proxy and was confirmed by Imişiker, Özcan and Taş (2015) and Aaron, Koesrindartoto and Takashima (2018). We adopt the PRIN score and is computed as follows:

$$PRIN_{stock\ i.broker\ j} = \frac{\text{Number of time broker } j \text{ trading as principal in stock } i}{\text{Number of times broker } j \text{ trade in stock } i} * 100\%$$

PRIN is constructed for each broker for respective stock i . For example, broker-1 has a PRIN of 1.28 in stock of j for entire trades in the sample while broker 2 has a mean PRIN of 3.91. Khwaja and Mian 2005 (p218) state that “*PRIN serves as a proxy for the extent to which a*

broker trading on his own behalf for a given stock (interpreted more broadly as the broker trading on behalf of one investor or a perfectly colluded set of investors)”. The authors state that PRIN orders brokers’ principalness within the same stock to the extent that a high PRIN value in stock i cannot be compared with a low PRIN value in stock j . This is because PRIN value is influenced by the principalness of the brokers as well as other factors specific to the stock e.g. liquidity and turnover. So, if there is limited trading in a particular stock, the broker who trades more often in that particular stock is likely to depict a higher PRIN relative to others. Alternatively, if there is infrequent trading, small brokers may appear with a larger PRIN while frequent trading by all brokers may show a small PRIN score, some sort of averaging out.

Table 3.4 below presents descriptive statistics for PRIN variable for 55615 observations computed on entire history of trades at broker level. This contrasts with studies by Imişiker, Özcan and Taş (2015) and Khwaja and Mian (2005) which use daily aggregates to compute daily PRIN scores.

Table 3.4: Descriptive statistics for PRIN Scores by stockbrokers and Type of Trade

Table 3.4 presents descriptive statistics for the explanatory variable, PRIN. It measures the frequency of broker $_j$ trading in stock $_i$ as a principal relative to broker $_j$ trading on stock $_i$. Broker-2 trades more frequently as a principal relative to other brokers with a mean of 3.91. Two brokers, broker-1 and broker-3, trade on average as principals closer to the market average. Overall, the level of principalness is approximately 1.2.

PRIN BY BROKER	Mean	Median	Minimum	Maximum
Broker-1	1.28	0.91	0	4.5
Broker-2	3.91	0.83	0	50
Broker-3	1.35	1.26	0	3.47
Broker-4	0.55	0	0	3.30
Overall PRIN	1.18	0.96	0.24	3.12
PRINsell	0.90	0.76	0	2.29
PRINbuy	1.48	1.13	0	4.15
PRINcycle	0.09	0.101	0	0.26

Our approach slightly varies from the broad interpretation by Khwaja and Mian (2005) study and others. Their interpretation potentially overweight the level of PRIN score compared to ours as we are exact by definition. This is because our scores exclude managed clients' accounts (often high profile and other corporates) where stockbrokers operating on the MSE have discretion. Thus, we consider purely self-trades by brokers. Our PRIN scores thus have an advantage of precisely attributing the level of price manipulation by principal brokers.

Aaron, Koesrindartoto and Takashima (2018) interpret PRIN as the likelihood of broker's manipulative trade in a particular counter. Imişiker, Özcan and Taş (2015) confirm the usage of PRIN scores. The authors posit that PRIN serves as a proxy for the extent to which a broker trades as a principal in a given stock. Additionally, PRIN provides a proportion of trades consistent with pump and dump manipulative scheme in a particular stock. PRIN scores range from 0 percent to 100 percent. It can be generally construed as a ratio of manipulated trades to total trades by a broker.

The next step is to compute the brokers profits. In order to test our hypothesis that brokers who trade on their own behalf earn more profits than outside investors, we construct a measure of profitability in a particular stock. Khwaja and Mian (2005) develop a measure styled annualized nominal rate of return

(ARR). It measures brokers earnings per year for a 100 units of average capital invested.

Imişiker, Özcan and Taş (2015) modify the proxy used by Khwaja and Mian (2005) by using actual prices against specified quantities and style their methodology annualized unbiased nominal rate of return (AURR hereafter). Khwaja and Mian (2005) utilize average price and aggregate daily quantities. Aaron, Koesrindartoto and Takashima (2018) study utilize both an annualized nominal rate of return (ARR) for each stockbroker as well as AURR. The interpretation is nonetheless the same. These studies show that an ARR measures the trading profits that a stockbroker generates per unit of capital invested. Thus, we follow their method by constructing an annualized nominal return (ARR) for entire trading history of each broker for every stock they trade in. Specifically, an ARR of 25% will be interpreted as a broker earning K25.00 in a year on average capital investment on every K100.00. We also follow Khwaja and Mian (2005) method of valuing end sample holdings by liquidating the end position using the end of sample stock price. The ARR measures gains from inter day trading. It ignores commissions and bid-ask spreads. The construction of the ARR measure is described below.

A table (see Appendix 1 for an example) is created for the entire trading history where a broker trades particular stock at a particular price on a particular day. We then compute for each day, the net shares of a given stock in a trading day acquired by the broker. The overall inventory is tracked by adding up all previous net trades.

In order to compute the annual rate of return, there is need to compute the net profit and the average capital required by the broker to generate such profit. The method considers net shares sold as revenue while net shares bought is treated as an investment. The net profit is then computed as the difference between revenue and investment, from the sum of revenue up to that point.

We then compute running profit or loss over entire period by differencing out the sum of investments from the sum of revenue up to each point. The running profit at the end of the period is the total profit/loss earned by the broker over the entire period. Then we compute the average capital needed by the broker over sample period i.e. value of net broker holdings less any profits accumulated up to the point, then weight it by the time. The overall rate of return is total net profit divided by gross capital used. Then the overall return is annualized to obtain the ARR measure.

The ARR represents profit generated by the broker for each account (See Descriptives of ARR in Table 3.5). Khwaja and Mian (2005) state that the ARR measure captures the trading profits generated by a stockbroker for each unit of capital invested. In computing the overall rate of return, the authors state that the total net profit is divided by the average net capital. Given that they mention that the average capital is computed from the value of net inventory holdings of a broker, the overall return is computed relative to gross capital.

Table 3.5 Descriptive Statistics ARR

Table 3.5 presents descriptive statistics for the dependent variable, ARR scores by brokers. It is a profit measure represented as percentage of capital. It measures the trading profit earned by broker per unit of capital invested.

Broker	Average Prin	Average ARR	Max ARR	Min ARR
1	1.5769	-0.10538	0.60	-0.45
2	1.1213	-0.3863	0.54	-4.25
3	1.76125	0.0958	0.33	-0.03

Following the construction of ARR, we identify outliers in all samples by boxplot procedure of Tukey (1977) to determine potential outliers. We then formally and statistically identify the outliers by employing Rosner (1975) test. As outliers have potential to bias our estimates, and so in order to address the robustness problem, we then winsorize the data by the methodology

of Nyitrai and Virág (2019) which entails replacing extreme values in the time series by their closest values. This entails simple winsorization at first percentile of the distribution. In the reconstructed data frame, approximately 8 percent of the observations are outliers.

In the next session we address the main question as to whether broker's trading profits from manipulated trades are higher than those earned by outside investors.

3.3.2.3 Basic Regression

In the previous section, we described the formalization of our main variable, PRIN and the dependent variable, ARR. The purpose of the study is to compare trading profits earned by principal brokers relative to intermediary trades. It should be pointed out that what brokers earn through principal trades is also considered earnings as such trades do not levy commission. In order to achieve this objective, having constructed the annualized nominal rate of return (ARR), we estimate a regression equation following Khwaja and Mian (2005), as below:

$$ARR_{\text{stock.broker}} = \alpha + \beta \cdot PRIN_{\text{stock.broker}} + \gamma S + \varepsilon_{\text{stock.broker}}; \quad \dots \quad (1)$$

where ARR is a profit measure represented as percentage of capital. It measures the trading profit earned by broker per unit of capital invested. PRIN is the measure of principalness; S represents stockbroker fixed effects. It is a matrix that contains stock dummy variable. ε is the error term. β measures the level of returns that principal brokers earn over intermediary trades (outside investors). Imişiker, Özcan and Taş (2015) posit that β is a monetary value of each additional percent of suspicious trade. The authors extend the model by including a variable $Volume_{\text{broker}}$ representing volume of stock traded as a control variable. The model also relates to Allen and Gale (1992) and Mei, Wu and Zhou (2005). The fixed effects, S enables the model to compare brokers within the same stock. It is expected that the results will show a pattern of principal trading over the period and a particular technique of trade-based manipulation.

3.4 Research Hypothesis

As explained earlier in Section 3.1, researchers such as Khwaja and Mian (2005), Imişiker, Özcan and Taş (2015) and Aaron, Koesrindartoto and Takashima (2020) document that brokers earn at least 50 percent higher annual returns than outside investors from manipulated trades. From a socio-political point of view, manipulation creates unequal distribution of wealth (Khwaja and Mian 2005; Aggarwal and Wu 2006). It is therefore important to investigate the extent to which misconduct by stockbrokers exists in LDCs. Policy makers ought to be

concerned if there are price distortions by market intermediaries. How fair is their trading practice? Do stockbrokers generate excess returns than outside investors?

In order to test the hypothesis that brokers who trade as principals earn higher profits through manipulative trading than intermediary trades, we compare their trading profits relative to outside investors. Thus, we analyze their trading pattern. More formally, we test the following hypothesis:

H₀: The annualized nominal rate of return (ARR) of brokers, as principals is 50 percent higher than that of intermediary trades.

H₁: The annualized nominal rate of return (ARR) of brokers, as principals is not 50 percent higher than that of intermediary trades.

3.5 Empirical Results

Table 3.6 below displays results of the regression in equation (1) run as ordinary least squares (OLS hereafter) and panel linear model with fixed effects model. The linear regression models the relationship between the level of principalness and the profitability. The OLS weighs each observation equally while the panel linear weighs each observation by the capital invested in the stock. The robust standard errors are in parenthesis.

The analysis considers data from 3 brokers as the fourth broker has nil ARR measures and so do not affect our results. The table shows that the coefficient of interest *PRIN* given by the linear panel model in column 2 is positive, suggesting that principal trades earn an annual return of 0.004 percent more compared to intermediary trades. The effect of this measure is however not significant at 5 percent level of significance. The R-squared shows that the level of principalness explains about 0.002 percent of variation. The results with robust standard error estimates are also not significant. These results show that no evidence for nonlinear association between principal brokers and profitability was found.

Table 3.6: Measurement of profitability of principal trades.

The table presents results of our regression which include fixed effects. Each observation is at the broker level. ARR is the annualized rate of return on the broker trades. PRIN is the level of principalness of the broker. The results show that the effect of PRIN is not significant at 1, 5 and 10 percent level. The observations cover period 2008 to 2019. There are no records for principal trades from period 1996 to 2007. The robust standard errors are in parenthesis.

	ARR, rate of return		
	<i>OLS</i>	<i>panel</i>	<i>coefficient</i>
		<i>linear</i>	<i>test</i>
	(1)	(2)	(3)
PRIN	-0.001 (0.01)	0.0004 (0.01)	0.0004 (0.0004)
Constant	0.01 (0.05)		
Observations	35	35	
R ²	0.0002	0.0002	

Significance level: * indicates significance at the 10 percent level, ** indicates significance at the 5 percent level while *** indicates significance at the 1 percent level

3.5.1 Test for sub periods of the state of the market

As shown in Table 3.6 above, the robust error correction test does not improve our results. We thus analyze the data in relation to the state of the market. Pagan and Sossounov (2003) define bull and bear markets as considerable periods of time when stock prices rise and fall. The authors state that these states of the market provide a framework for analyzing the phases of the market. Thus, we classify the data into bull and bear periods. In this connection therefore, we follow the methodology of Cooper, Gutierrez and Hameed (2004). The authors employ a 3-year moving average of returns of a value weighted index to determine the state of the market. If the 3-year return of the Malawi All Share Index is positive, the state of the market is categorized as bull. On the other hand, it is categorized as bear, if the return is negative. We also consider a 2-year and 1- year moving average return as robustness check to this

methodology. Thus, we construct annualized nominal rate of return (ARR) for each state of the market. Table 3.7 below shows dates for states of the market.

Table 3.7: States of the market

Table 3.7 shows classification of bull and bear periods. The market experienced more bull periods than bear runs. If the 3-year return is positive, the state of the market is categorized as bull, otherwise it is a bear period. The method is replicated for 2 year and 1 year moving averages and marked accordingly.

3yr moving average				2yr moving average				1yr moving average			
Bull		Bear		Bull		Bear		Bull		Bear	
start date	end date	start date	end date	start date	end date	start date	end date	start date	end date	start date	end date
29/10/2010	28/08/2011	31/03/2011	31/01/2012	30/10/2009	26/02/2010	31/03/2011	31/10/2011	31/10/2008	27/02/2009	31/03/2009	31/03/2011
21/02/2012	28/09/2020			30/11/2011	31/03/2016	29/04/2016	30/06/2017	29/04/2011	30/11/2015	31/12/2015	28/02/2017
				31/07/2017	30/04/2020	29/05/2020	28/09/2020	31/03/2017	30/04/2019	31/05/2019	31/10/2019
								29/11/2019	28/09/2020		

The ARR's are computed for each broker during each period. They are then grouped into either bull or bear period and formally tested. The results in Table 3.8 show that principal brokers earn a negative annual rate of return of 0.065 percent lower than outside investors during periods of declining prices while during bull period they earn 0.055 percent lower annual return than intermediary investors. The results with fixed effects show that principal brokers earn a negative return of 0.06 percent lower return during bear period and a negative 0.069 during bull periods. The results are not significant at 5 percent level of significance. The results show there is no evidence that principal brokers earn higher annual returns than intermediary investors. In fact, they do earn lower return although this is not significant.

Table 3.8: Regression Results of states of the market

Measurement of profitability of principal trades during bull and bear periods. Regression results include fixed effects There are 2 sub samples generated from compiling annualized annual returns earned during bear and bull periods. The results with fixed effects show that principal brokers earn a negative annual return of 0.06 percent lower during bear periods and earn a negative return of 0.069 percent lower during bull period. The results show that the effect of PRIN is not significant at 5 percent level. The robust standard errors are in parenthesis.

	ARR rate of return					
	Bear period			Bull period		
	<i>OLS</i>	<i>panel</i>	<i>coefficient</i>	<i>OLS</i>	<i>panel</i>	<i>coefficient</i>
		<i>linear</i>	<i>test</i>		<i>linear</i>	<i>test</i>
	(1)	(2)	(3)	(4)	(5)	(6)
PRIN	-0.065	-0.060	-0.060			
	(0.044)	(0.037)	(0.036)			
PRIN				-0.055	-0.069	-0.069
				(0.037)	(0.036)	(0.038)
Constant	0.193			0.093		
	(0.095)			(0.069)		
Observations	9	35		35	35	
R ²	0.233	0.074		0.061	0.103	

* indicates significance at the 10 percent level, ** indicates significance at the 5 percent level while *** indicates significance at the 1 percent level

3.5.2 Test for Pump and Dump manipulation scheme

Putnins (2012) state that manipulative runs where the broker takes a long or short position, artificially influences the price to rise or decline to attract liquidity from trend chasers to the stock before reversing their position at either a high or low price are common. This type of run is typically called a pump and dump manipulative scheme. Khwaja and Mian (2005) states that this trading pattern is prevalent in emerging countries. The trading mechanism assumes existence of trend chasers; and that a number of brokers act in concert unlike a single broker doing so.

We therefore test for this mechanism by examining whether brokers are buying low and selling high in order to make profits. Like in Khwaja and Mian (2005) we classify each stock date with a state variable P_b and P_s where P_b and P_s refer to the overall PRIN category of buyers and sellers respectively trading in that particular stock on the material date. Thus, we generate variables for each state depending on whether the brokers are trading amongst each other at low prices (HH) and where intermediaries are trading amongst each other at high prices (LL). These states refer to a trading strategy, for example HH state means that the average PRIN of the brokers buying the stock's stock that month is high, and the average PRIN of the brokers selling the stock that month is also high. The high and low PRIN have been determined by the median i.e. whether the PRIN is either above or below the median. We then for each month construct a portfolio based on the respective state. For example, the HH portfolio will include all the stocks that the average PRIN of the brokers buying and the average PRIN of the brokers selling that stock the previous month is high. We then regress these observations (stock returns) against specific level of principalness (P_{buy} and P_{sell}). In other words, we regress stock return against the market return for each state of the market. The results are presented in Table 3.9 below. The results show that principal brokers earn excess annual return of 0.002 percent higher when they trade amongst themselves. The results however are not statistically significant.

Table 3.9: State contingent returns

Columns 1-4 regress 306 monthly excess or above market returns from using different strategies. A strategy X refers to holding each month a portfolio that contains all the stocks with a state X the previous month. A stock is in HH state in a given month if the average PRIN of both buyers and sellers of the stock that month is high (when mostly the brokers trade against each other that month). A stock is in LL state in a given month (the average PRIN of both buyers and sellers of that stock is low i.e. mostly the intermediaries are trading amongst themselves that month. LH and HL have similar definitions, differing only in that the state next month is neither LL nor HH respectively. The robust standard errors are in parenthesis.

	Monthly excess return using strategy			
	HH	LL	LH	HL
	(1)	(2)	(3)	(4)
Constant	0.002 (0.008)	-0.001 (0.009)	0.011 (0.009)	0.002 (0.009)
Observations	306	306	306	306
R ²	0.069	0.069	0.074	0.067

* indicates significance at the 10 percent level,** indicates significance at the 5 percent level while *** indicates significance at the 1 percent level

3.6 Previous findings

Several studies in emerging markets have shown evidence of trade-based manipulation. As mentioned in literature review, there is dearth of evidence that documents presence of market manipulation in least developed countries. It was hypothesized that brokers use their principalness to generate higher profits than outside investors. What is surprising is that given the small size of the market, illiquid stocks, few brokers and stocks, and that literature shows asymmetry of information and that brokers use their power to manipulate prices, the study finds no evidence of profitable manipulation indicating that market efficiency does not appear to be negatively affected by manipulation.

There is some empirical support that manipulation cannot systematically generate profits. For example, Jiang, Mahoney and Mei (2005) investigate information content of stock pools. They find that pool stocks displayed increased return continuation conditional on high trading

volume. This was motivated by informed trading. They find that systematic trading was not a significant problem at the New York Stock Exchange in the 1920's. They explain that the disclosures that existed at the time, relating to size, liquidity and information might have been sufficient to make manipulation difficult.

Camerer (1998) investigates price manipulation through field experiment of odds (prices) in horse races. The study finds that bettors did not systematically affect the changes on the attack horse relative to controls. The study explains that the size of the bets might have been insignificant to be noticed or the market may have been large to be influenced. The study concludes that the market may have simply aggregated information to enable operators ignore unusually large bets.

A possible explanation for the results of our study may be the lack of adequate number of players in the market which makes them noticeable. It is probable that brokers see what the other is doing. Given their limited numbers, brokers are easily visible to the exchange such that manipulation would be noticeable and so brokers probably find it difficult to engage in misconduct. Stigler (1964) posits that industry profits are maximized when firms act in concert. This implies that collusion is highly prevalent where there is a small number of competitors and may inhibit strategic behavior. It is also likely that the regulation may be tight to discourage misconduct.

Geanakoplos (1992) posits that the absence of speculation may be due to common knowledge i.e. when it is common knowledge that agents are rational and optimizing, variation in information amongst the agents not only discourage trading but potentially suppresses trading which would have taken place if there had been symmetric information. So, it is probable that common knowledge leads brokers to not cheat against each other. Abrantes-Metz, Kraten, Metz and Seow (2012) investigate the libor manipulation. They do not find evidence consistent with material manipulation of the US dollar 1-month libor rate. They explain that the nature of the composition of the banking group from which the libor was derived might generate an opportunity for collusion if the majority of the banks tend to be net borrowers or lenders.

Our results are different from those obtaining in emerging markets, for example Aaron, Koesrindartoto and Takashima (2018), İmişiker, Özcan and Taş (2015), Huang and Cheng (2015), Azad, Azmat, Fang, Edirisuriya (2014), Comerton-Forde and Putniņš (2014) and İmişiker and Taş (2013). Given the level of development in emerging markets, there are more brokers and voluminous transactions which are associated with high liquidity. Aggarwal and

Wu (2006) find that manipulated stocks are characterized by high volatility, high returns and increasing liquidity during the manipulation period. This does not appear to obtain in our case. The same is echoed by the study of Imişiker *et al.*, (2015) which finds that stock liquidity and turnover are consistent with the pump and dump manipulative scheme. Studies by Aggarwal and Wu (2006) and Khwaja and Mian (2005) suggest that manipulation is undertaken jointly by a number of parties. This does not appear to obtain either in the least developed country.

Khwaja and Mian (2011) assert that rent seeking results into weakening governing institutions. They further add that developed countries have stronger institutions which provide robust checks and balances relative to developing countries. This suggest that there is therefore limited rent seeking behavior in developed countries relative to developing countries. Our finding therefore implies that given the size of the market and its prevailing institutions, existence of the rules probably enhance the integrity of the brokers and potentially limit misconduct in the financial market. This is amplified by the legislation that motivates brokers to supplement income from other permissible activities. For example, the Financial Services (*Establishment and Operations of Brokers and Dealers*) Directive, 2015 states as follows:

Section 14(11) A licensed broker or dealer shall not engage in money market business other than securities issued by the Malawi Government and the Reserve bank, unless exempted by the Registrar.

This provision allows brokers to engage in limited fund management where they generate additional income. Thus, they probably live on it sufficiently to discourage them from manipulative action.

The implication of the finding is that existence of the regulation may have an impact on the integrity of the brokers and potentially affect their trading conduct. Thus investors may potentially be attracted to LDCs. Drake (1977) states that confidence is the most impediment to development of capital markets in the LDCs. The result may also be attractive to interested researchers who may wish to explore more about LDCs.

3.7 Summary and Conclusion

In this investigation the aim was to assess the profitability differentials between principal brokers and outside investors in a least developed country. The study analyzed trading pattern to compare trading profits between market intermediaries and outside investors. Specifically,

the study examines the relationship between level of principalness by brokers and their trading profits. This is important because of negative welfare transfer of economic benefits.

The results of this investigation shows that there is no evidence that brokers manipulate the market. Given that theory informs us that brokers use information asymmetry and their position to manipulate stock markets, our results contradict the theory. An explanation of this finding is that limited numbers of brokers and thin trading in the market, would probably make price manipulation noticeable and so brokers find it difficult to engage in it. It is also probable that since brokers are allowed by regulation to engage in limited fund management where they generate supplementary income, they probably live on sufficiently to discourage them from manipulative action.

An implication of the finding is that market intermediaries in Malawi market probably do not generate higher profits than outside investors enabled by the integrity of the brokers and motivating legislation. The study documents empirical evidence to the body of literature on price destabilization.

4.0 Financial market efficiency in a least developed country and the Disposition Effect.

4.1 Introduction

The neoclassical theory of Finance postulates the dominant hypothesis that markets are efficient, based on the premise that investors are perfectly rational. However, Brown, Chappel, Rosa and Walter (2006) posit that recent studies in psychology have shown that investors have behavioral biases which induce trading patterns which violate the principles of rationality. We study the pervasiveness of one such bias, termed disposition effect, which according to Shefrin and Statman (1985) is defined as the tendency by investors to sell winners too early and hold onto losers for too long. Odean (1998), Weber and Camerer (1998) and Frydman and Rangel (2014) observe that disposition bias is associated with suboptimal investment performance. Disposition effect is costly for investors [(Coval and Shumway (2005) and Choe and Eom (2009))]. However, there is continuing debate among researchers about the underlying causes of the behavioral bias.

We study disposition effect because it matters for academicians, investors and regulators. Theory explains that disposition effect justifies observed behavior such as momentum trading [(Jegadeesh and Titman (1993), Rouwenhorst (1998))]. Studies such as Grinblatt and Han (2005) argue that disposition effect is the main driver of momentum profits. It has been documented that investors can exploit patterns and build better portfolios [(Heath, Huddart and Lang (1999))]. For example, studies by Heath, Huddart and Lang (1999) document that option traders react to past prices. Further, Dhar and Zhu (2006) posit that rational investors can profit off noisy investors. The study is of interest to the wider economy for policy makers. Given that disposition effect affects prices [(Coval and Shumway (2005))], it therefore follows that resource allocation would be impaired.

Disposition effect has been investigated in various economic settings. For example, Lakonishok and Smidt (1986), Ferris, Haugen and Makhija (1988), Odean (1998), Shapira and Venezia (2001) have investigated the stock market. Locke and Mann (2005) and Coval and Shumway (2005) investigate the futures market. Genesove and Mayer (2001) investigate the residential estate. Weber and Camerer (1998) investigate disposition effect through laboratory experiments.

There are several studies that have investigated the USA markets such as Lakonishok and Smidt (1986) and Ferris, Haugen and Makhija (1988). Disposition effect has also been examined outside the USA. For example, Australia (Brown *et al.* 2006), China (Chen, Kim,

Nofsinger and Rui 2007), Finland (Grinblatt and Keloharju (2001), Kaustia (2010), Lehenkari (2012)), Israel (Shapira and Venezia (2001)), and Taiwan (Barber, Lee, Liu and Odean (2007)), France (Booell-Gunesh, Broihanne and Merli (2009)), Portugal (Leal, Rocha Armada and Duque (2010)), Sweden (Calvet, Campbell and Sodini (2009)), and Korea (Choe and Eom (2009)). While most of the studies have focused on finding the investor characteristics that are related with disposition effect, for example investor sophistication, experience in Feng and Seasholes, (2005) and Dhar and Zhu (2006), very few studies have investigated the potential causes of disposition effect. The studies such as Odean (1998), Weber and Camerer (1998), Barber *et al.* 2007, and Lehenkari (2012) show debates about the potential causes of disposition effect. Thus, the underlying causes remain an open question.

The theories that are tested in developed countries are consequently accepted and applied. It is our motivation that theories advanced in developed countries will not directly apply to least developed countries (LDC's hereafter). The least developed countries vary characteristically from developed countries with respect to market sophistication in terms of traded instruments and traders; investor literacy levels, market liquidity, informational systems and adequacy of regulation. Most of the markets are rudimentary and have less experienced individual investors, yet have recently registered huge growth. According to the portal of the African-Exchanges, the Malawi Stock Exchange ranks third in the top five exchanges by market capitalization amongst African Stock Exchanges as of end December 2020 yet most of investors are novice. Studies have shown that little trading experience leads to susceptibility to behavior biases. Studies by Feng and Seasholes (2005), Dhar and Zhu (2006), and Muhl and Talpsepp (2018) have documented exhibition of disposition effect among individual investors. This effect is very likely to be heavily manifested in least developed countries given low literacy levels, unsophisticated investors and poor information systems.

Grinblatt and Keloharju (2001) and Kaustia (2004) posit that disposition effect is an application of prospect theory of Kahneman and Tversky (1979). The theory states that investors evaluate gains and losses relative to a reference point, often a purchase price. This implies that investors who register gains are risk averse while those who register losses are risk loving in an effort to break even. There is evidence from stock markets by Odean (1998) and Shapira and Venezia (2001). On the other hand, Hens and Vlcek (2011) posit that the sale of winning stocks and holding of losing stocks is completely a rational scenario. The study articulates that for a utility maximizer who has constant relative risk aversion rebalances a fixed-mix portfolio strategy in a scenario where the investment opportunity is constant in line with economic theory such that

if an asset's price increases (decreases), the investor would decrease (increase) their portfolio holding to rebalance to constant weights. However, study by Odean (1998) finds that investors have a tendency to hold onto losers even when controlling for rebalancing.

Kaustia (2004) posits that investors shun crystallising losses. This notion is explained in theory by loss aversion in prospect theory of the Kahneman and Tversky (1979). The study postulates that the relationship between an asset's price to an investors reference price affects the investor's utility asymmetrically i.e. the investor will be risk-averse in the domain of gains but risk-seeking in the domain of losses.

Given a standard expected utility theory and without capital gains tax, it is a rational decision for an investor to hold onto winning stocks to increase profits and to cut losses by disposing off losing stocks (Altman, 2010). There seems to be a school of thought among researchers that if disposition effect holds then there will be momentum profits [(Grinblatt and Han 2002)]. However, Barber *et al.*, (2007) document prevalence of disposition effect amongst Taiwanese investors, by showing that the effect does not always lead to momentum profits. This implies that it is not always the case that disposition effect will predict momentum profits.

Most studies have investigated disposition effect in USA and other developed countries where it is challenging to extract the disposition effect from tax effects which influence selling decisions. The influence of taxation on selling choices has been documented by Badrinath and Lewellen (1991). In Malawi however, according to the first schedule of the Taxation Act of 2020, the capital gains tax²² provisions for stocks listed on the stock exchange apply to trades executed within a year and not thereafter. For example, if an investor buys a stock and sells it within a 12-month window from date of purchase, they are subjected to capital gains tax, if they sell in the 13th month, they are not. This was mooted as an incentive to encourage investors to consider placing funds for longer horizons beyond a year, compared to investments in money markets. However, for reasons not explained by the tax authorities, the capital gains tax is not administered. Thus, we consider the practical existence of the Malawi stock market as free of capital gains tax. This enables us to factor out any arguments that tax effects would influence selling decisions and so differentiates our study from several previous studies. Boolell-Gunesh, Broihanne and Merli (2009) examine the influence of tax regime on investors selling behavior in France and finds that there is no impact at all.

²² This has been the case since 1992 including revisions of 1993, 1995, 1997, 2012 and 2016.

Shapira and Venezia (2001) analyze behavioral patterns of types of round trips trades namely simple and sequential. Simple rounds are those involving one buy and one sell order while sequential deals involve more than one sale or buy trades. Shapira and Venezia (2001) test for difference in disposition effect between the groups (individuals and professional group) and find that disposition effect largely emanates from simple rounds relative to sequential rounds.

The foregoing studies clearly suggest that disposition effect has been extensively studied in developed countries. However, there is no research study on least developed countries. We fill this gap by studying investigating trading records of investors between 2013 and 2019. We are not aware of any other study in least developed countries.

We contribute to the body of knowledge on investor selling behavior by documenting evidence. This allows insights into disposition effect in LDCs where there is dearth of research. Muhl and Talpsepp (2018) study suggests that different market conditions are an important explanatory source of investor behavior. The Malawi market has generally been an upward moving market since 2013, suggesting theoretically rising prices. It has been documented that disposition effect leads to suboptimal performance [Odean (1998), Weber and Camerer (1998), and Frydman and Rangel (2014)]. The findings will also contribute to the growing field that challenges market efficiency through possibility of momentum profits [(Grinblatt and Han (2005) and Barber *et al.*, (2007)))] as well as price implications [Frazzini (2006)].

4.2 Efficient Markets and Disposition effect

The commanding hypothesis in finance literature is that markets are efficient based on two key assumptions: rationality of agents and riskless arbitrage. It is important to highlight the concept of rationality with respect to financial markets. As stated earlier in chapter 2, the assumption is that investors are rigorously rational agents suggesting that they are relatively homogenous in their expectations with each one of them maximizing their subjective probability and bearing consistent beliefs with respect to the distribution of the factors affecting returns which they update using Bayes²³ rule [(Barberis and Thaler, 2002)]. Thus, Bayesians believe that estimation involves continually updating and sharpening subjective beliefs about the state of the world. It suggests that people update beliefs correctly based on probability distributions. Put differently, market agents see correct signals and that they have consistent

²³ According to economists, rational learning is undertaken in accordance with Bayes rule which is a probability-based rule to infer the outcome of an event given the occurrence of another.

beliefs. In addition, agents have superior foresight such that they rarely make mistakes, otherwise their mistakes are not systematic.

Behavioral finance posits that research findings from cognitive psychology evidence demonstrate that human behavior is influenced by bias and heuristics; and also imply a less rational world for investor behavior. Such findings argue that human behavior can therefore not be construed as homogenous. Furthermore, factors such as levels of education, risk preferences and how information is processed affects how decisions are made. More so, under uncertainty, investor behavior cannot be easily predicted as Shiller (1998) opines that research ought to maintain an appropriate perspective of human behavior and its complexity.

Shleifer (2002) argues that competitive financial markets are populated by both fully rational agents and others who are either biased or not rational at all. The interaction of these agents affects security prices to an extent that the notion of efficient markets may not obtain because investment decisions are affected by the human element. Black (1986) hypothesized that asset prices incorporate information from both well informed investors as well as uninformed investors (noisy traders).

Fama (1965, 1970) and Malkiel (2003) made a compelling case that irrational investors can not significantly affect the price formation process (in the long run) as they would face rational speculators who would counter all efforts by such noisy traders by moving prices towards the fundamentals. They also argued that the speculation by irrational investors would not be destabilizing. Further, the authors argue that irrational investors would lose their money and eventually exit the market. Hirshleifer (2001) has shown that investors are prone to behavioral bias, to an extent that it raises potential threat to financial markets [(Fama 1970)]. While studies such as Grinblatt and Keloharju (2001), Choe and Eom (2009), Shapira and Venezia (2001) have shown that individual investors are prone to disposition effect, other studies such as Coval and Shumway (2005) and Chen, Kim, Nofsinger and Rui (2007) find that professional investors less frequently exhibit the disposition bias. Thus this behavior appears to be present among individuals as well as professional investors.

4.3 Dealing with Disposition effect

Theoretical literature suggests that investors can attenuate disposition effect by practising broad framing i.e. they can view all decisions comprehensively. Studies have shown that both individuals and institutions are prone to disposition effect [Shapira and Venezia (2001), Barber *et al.*, (2007) and Lehenkari (2012)]. On individual level, investment decisions are often driven by fear of regret or pride, or the belief in mean reverting prices. However, investment decisions

ought to have reasonable basis as opposed to one-off win or loss. Literature suggests that if a number of people have a dispositional bias, then it can have a great systemic impact. Study by Singal and Xu (2011) show that at a firm level, a number of mutual funds face the threat of existence. This is dangerous for a nascent market which has a small mutual fund industry. The industry can potentially disappear.

Wierzbicki and Seidens (2018) suggests that hedonic framing, a mental approach can be utilized to minimize disposition effect. It is a technique that requires an investor to frame thoughts positively in order to respond to gains and losses. For example, if the investor faces a choice between one large gain and numerous small gains, they should opt for numerous small gains. On the other hand, if faced with one large loss and numerous small losses, then they should frame their thoughts as one bad loss. This helps to feel less pain when faced with negative outcomes.

Literature also suggests that emotions and irrationality can be removed from decision making process by adopting a rule-based system. This is however possible due to learning and experience. Study by Weber and Camerer (1998) finds that automatic selling of stocks reduces the tendency to ride losers and sell winner. This suggests that automatic selling of stocks attenuates disposition effect. In addition, stop loss orders, which have predefined parameters may be used to attenuate disposition effect. For example, Fischbacher, Hoffmann and Schudy (2017) provide experimental evidence that automatic selling devices facilitated an increase in the proportions of losers realized but did not influence the proportion of winners realized.

Further, Muhl and Talpsepp (2018) study shows that learning can reduce disposition effect. The study documents evidence that as investors gain experience, they reduce the tendency to hold onto losses during a bear period. This is possible due to feedback and financial consequences of losses during a downturn. Frydman and Rangel (2014) find that individuals who were exposed to the stocks' purchase price exhibited disposition effect while the other group that had a less salient purchase price information registered a 25 percent decline in disposition effect. This suggests that a nudging approach may minimise behavioral bias in individuals.

Empirical studies such as Weber and Camerer (1998), Grinblatt and Keloharju (2001), Shapira and Venezia (2001), Feng and Seasholes (2005) Brown *et al.*, (2006), Dhar and Zhu (2006), Chen *et al.*, (2007), Boolell-Gunesh, Broihanne and Merli (2009), and Seru, Shumway and Stoffman (2010) document evidence that disposition effect may be attenuated by

sophistication, trading experience or adopting trading strategies. For example, Locke and Mann (2005) find that adherence to exit strategies through speed of execution and avoidance of riding losses for too long are critical to the success of future traders. The study suggests that investors need to put in place a discipline approach to use predetermined trade exit strategies to mitigate potential losses. Dhar and Zhu (2006) find that financial literacy factors such as income and occupation status lowers the tendency to realize gains faster than losses. Feng and Seasholes (2005) show that a combination of sophistication and trading experience attenuates realization of losses.

These studies suggest that psychological techniques (hedonic framing), trading strategies (automatic selling devices) and learning (experience and sophistication) can attenuate disposition effect to improve performance.

4.4 Data and methodology

The aim of the study is to investigate whether investors in Malawi exhibit the tendency to realize gains sooner than they crystallize losses; and to explain potential causes. The study addresses the primary question by utilising the methodology of Odean (1998).

4.4.1 Data

The data set comprise all investors trading accounts from four (4) brokerage houses. They comprise of all accounts from 2013 to October 2019, including both sales and purchases. The data covers all trades in the market during the sample period. The data are obtained from the regulatory authority, which is also the central bank. The data has been structured into two files, an investor file and prices file. The investor file contains records of all transactions from January 2013 through October 2019. The file has 22, 346 transactions where each record is made up of an account identifier, date of trading, buy-sell indicator, quantity trade, price and the stock code. The price file has 5633 records. Each record comprises a stock code, date of transaction and price. Table 4.1 shows that there are 2422 individual investors and 193 institutional investors during the entire sample period. The average number of trades per individual investor was 26.2 while for institutional investors was 648.2 during entire period.

Table 4.1: Descriptive statistics

<i>No of Investors</i>	Entire period	2013-2016	2017-2019
Individuals	2422	1272	1150
Institutional	193	83	110
<i>No of trades</i>			
Individuals	13114	6637	6477
Institutional	9232	4421	5011
<i>Average No of trades</i>			
Individuals	26.2	27.5	24.9
Institutional	648.2	628.9	664.5

The analysis focuses on investor accounts that trade at least twice during sample period and so only comprise of stock trades. Like in the study of Odean (1998), we create an account for each investor and for each day of the sampling period. The trades are then netted on the same day for each asset for any investor. All sales for which we have no corresponding purchase are ignored, just like in Odean (1998).

4.4.2 Methodology

The study follows the methodology of Odean (1998). It classifies four determinants of investors' wealth by categorising the number of stock positions namely sold for gain, loss, not sold but gain and not sold but loss. The gains and losses are computed relative to the purchase price. The actual trades are labelled realized gains and realized losses. The stocks that have not been sold for gain or loss are labelled paper gain or paper loss relative to the day's closing price as a hypothetical selling price. A total count of gains (loss) is made by summing up realized gains (losses) and paper gains (losses). The methodology has also been deployed by Barber *et al.*, (2007), Frydman and Rangel (2014), Rau (2015) and Fischbacher, Hoffmann and Schudy (2017). It assumes that investors use the purchase price as a reference point to determine gains or losses.

The model of disposition effect predicts that investors realize more gains relative to the number of gains available for realization and realize fewer of the losses relative to number of losses available. As in Odean (1998), we calculate realized gains and realized losses for each investor and then aggregate over all investors and trading days for the entire sample period. Barber *et al.*, (2007) aggregate for all days. Then we set up the following proportions:

$$\text{Proportion of Gains Realized (PGR)} = \frac{(\text{Realized Gains})}{(\text{Realized Gains} + \text{Paper Gains})} \dots\dots\dots (1)$$

$$\text{Proportion of Losses Realized (PLR)} = \frac{(\text{Realized Losses})}{(\text{Realized Losses} + \text{Paper Losses})} \dots\dots\dots (2)$$

We then compare the differences between PGR and PLR. The difference between the average PGR and PLR for each category is tested for statistical significance using a one tailed test. A significant difference suggests that on average investors are willing to realise one element over another. For example, if PGR is significantly different from PLR, then it means investors realize more gains relative to losses. Thus, PGR greater than PLR will demonstrate disposition effect. It implies owners of those accounts exhibit disposition effect.

Rau (2015) state that disposition effect measures take values between -1 and 1. Investors who score a value of 1 show that they realize gains more readily than losses. The opposite holds for scores of -1 i.e such investors realize losses readily than they realize gains. A score of zero suggests that there is a balanced proportion of PGR and PLR which means that such investors do not exhibit disposition effect. Odean (1998) finds that on average investors realize 14.8 percent of gains available for realization while only 9.8 percent of losses are realized.

4.5 Research Hypothesis

The study aims to test for the disposition effect in a least developed country, i.e. Malawi by examining trading behavior of both retail and institutional investors. The research question is : Do investors in the Malawi market exhibit the tendency to sell winning stocks more readily than losing stocks? Odean (1998) questions the adequacy of examining the number of securities sold for gains versus the number sold for losses and suggests that the analysis must examine the frequency with which investors sell winners and losers relative to their opportunities to sell each. Therefore, the hypothesis is stated in respect of realization rates for gains and losses. The null hypothesis is that investors do not have a disposition to sell winning stocks more readily than losing stocks as below:

Hypothesis 1 : *Proportion of Gains Realized > Proportion of Losses Realized (for the entire year)*

The null hypothesis is mathematically represented as below

$$H_0: \text{PGR} \leq \text{PLR}$$

While the alternative hypothesis is

$$H_a: \text{PGR} > \text{PLR}$$

The second hypothesis is that due to tax effects investors are more willing to sell losers in June²⁴ and less willing to sell winners than during the rest of the year (July to May). It is represented mathematically as :

Hypothesis 2: *Proportion of Losses Realized – Proportion of Gains Realized in June > Proportion of Losses Realized – Proportion of Gains Realized in July to May*

The null hypothesis is presented below:

$$H_o : (\text{PLR} - \text{PGR}) \text{ in June} \leq (\text{PLR} - \text{PGR}) \text{ in July to May}$$

The alternative hypothesis is as below:

$$H_a : (\text{PLR} - \text{PGR}) \text{ in June} > (\text{PLR} - \text{PGR}) \text{ in July to May}$$

The study examines each trading account in chronological order by constructing for each date a portfolio of securities for which the purchase date and price are provided. Given that the portfolio is only part of each investor's total portfolio, there is a possibility that there are securities purchased prior to 2013 whose purchase price is not available. It is also possible that investors may have other securities portfolios that we do not consider. However, our selection of the sample period covers a large part of the stock exchanges active trading history and so like in Odean (1998), we do not bias partial portfolios towards stocks where investors display disposition effect.

Given that Malawi market is characterised by low liquidity, few trading instruments, less sophisticated investors, inadequate information systems and regulation, the study expects to find exhibition of disposition effect, considering that empirically and experimentally, Odean (1998) and Weber and Camerer (1998) have documented it in developed countries.

The study examines 625 (for 2013 to 2019 data) accounts which trade in 15 stocks for a total of 22,346 transactions. Like in Odean (1998), the study does not consider investor accounts that have single trades. It considers portfolio that have at least two or more stocks. In order to determine a realized gain or loss, the selling price for each stock sold is compared to its average purchase price for each day that a sell trade is recorded. Each stock that is in the portfolio at the beginning of the day but is not sold by the end of trading day is considered a paper gain or

²⁴ The financial year of the Malawi government runs from July to June. It will however change from 2021 to run from April to March 31. This change does not affect our analysis.

paper loss or none of the two. To determine if it is a paper gain or loss, the study compares the high and low price for that day to its average purchase price. A paper gain is counted, if both the stocks daily high and low are above its average price otherwise a paper loss if its below the average purchase price. If the stock's average purchase price lies between the high and the low, neither a gain nor a loss is counted. If there is no sale on a particular day in an account, no count for either realized or paper gain or loss is made.

Odean (1998) states that a test of the disposition effect is a joint test of the hypothesis that investors dispose of gains quickly than losses and of the specification of the reference point from which gains and losses are determined. Studies such as Barber *et al.*, (2007), Feng and Seasholes (2005) and Grinblatt and Keloharju (2001), state that alternative reference points include average purchase price, the highest purchase price, first purchase price or the most recent purchase price. This study utilises average purchase price as the reference point. The study controls for influence of time periods and investor characteristics; partial sales; new purchases; investor horizon; and trading costs.

4.6 Empirical Results

Table 4.2 reports proportions of gains realized (PGR) and proportions of losses realized (PLR) realized for the entire year, for June and for July through May. The results show that for the entire year investors realize a higher proportion of their winners than of their losers. For Hypothesis 1, the null hypothesis can be rejected with a high degree of statistical significance. A one tailed test of the first null hypothesis, $PGR \leq PLR$ is rejected with a t -statistic greater than 2.43. This means that there is evidence to support the disposition effect. The Malawian investors realize their gains earlier than they realize their losses. In respect of realization rates, on average investors are 37 percent more likely to sell stocks that register gains than they sell stocks that record losses.

A one tailed test of the second null hypothesis, $PLR - PGR \text{ in June} \leq PLR - PGR \text{ in July to May}$ is not rejected, as t -statistic of 0.40 is not significant. This means that there is no evidence to support an assertion that investors realize more losses in June, a tax period, than at any other time (July to May) during the year. In accordance with Odean (1998) the tests consider each transaction, whether a sale for a gain (loss) or paper gain (loss) on the day of a sale as separate

independent observations²⁵. This has also been followed by Leal, Rocha Armada and Duque (2010) and Boolell-Gunesh, Broihanne and Merli (2009).

Odean (1998) argues that the independence assumption may not perfectly hold, however given our relatively fewer observations and sparse trading, it is argued that decision not to sell on a particular date may likely be independent of a decision to sell on another particular date due to time period and possible influencing or changing informational factors that could come in during the time period. Therefore unlike in Odean (1998) the *t*-statistics are not extremely high. Like in Odean (1998), however the study conducts an alternative test to examine the perspective of criticality of independence assumption. Instead of independence at transactional level, it is assumed that there is independence at account level. Thus, it is assumed that the proportions of gains and losses realized in each investor account are not influenced by those realized in other accounts. PGR and PLR are then estimated for each account and their difference, PGR-PLR is calculated for each account. The study ignores all accounts whose denominator for either PGR or PLR is zero, just like in Odean (1998). Thus, the study has 625 accounts relative to Odean (1998) which has 1893 accounts. The results are presented in Table 4.3. The average PGR is 0.096 the average PLR is 0.068 and an average PGR-PLR is 0.028. The hypothesis that the mean of PGR-PLR is less than or equal to zero is rejected with a *t*-statistic of 2.672. This means that there is evidence to support disposition effect even after considering transactions at account level. Odean (1998) states that the alternative test controls for dependence brought about by common information. Thus sales are considered if no other sale of similar stock occurred within a period of seven days. However Odean (1998) cautions that this alternative method weights each account equally unlike the other method which treats each account by the number of realized gain and unrealized gains and losses in the respective account. The adoption of the alternative method of similar account treatment has an implication of assuming that the computed PGR and PLR as homoskedastic when they are actually otherwise. Odean (1998) argues that although this alternative method has a downside, it is useful to demonstrate that even after adopting a different set of independent assumptions, the primary result of the study still holds.

²⁵ The *t*-statistic in Table 1 utilize the standard error for the difference in proportions PGR and PLR computed as

$$se = \sqrt{\frac{PGR(1 - PGR)}{n_{r_l} + n_{p_g}} + \frac{PLR(1 - PLR)}{n_{r_l} + n_{p_l}}}$$

where n_{r_l} , n_{p_g} , n_{r_l} , and n_{p_l} are the number of realized gains, paper gains, realized losses and paper losses.

The results in Table 4.2 assume independent observations at transactional level while alternative results assume independence at account level. In the alternative approach, the realized and paper gains, and realized and paper losses are totalled before computing the PGR and PLR. The difference between PGR and PLR is computed for each account. This approach is adopted throughout the paper.

Table 4.2: PGR and PLR for the Entire Data Set

The table compares the combined Proportion of Gains Realized (PGR) to the combined Proportion of Losses Realized (PLR), where PGR is the number (count) of realized gains divided by the sum of realized gains and number of paper gains, and PLR is the number of realized losses divided by the sum of realized losses and paper losses. Realized gains, paper gains, realized losses and paper losses are aggregated over time (2013 to 2019) and across all accounts in the data set. PGR and PLR are reported for the entire year, for June only and for July through May. There are 2104 realized gains, 1956 realized losses, 17123 paper gains and 16408 paper losses for the entire year. For June, there are 107 realized gains, 49 realized losses, 792 paper gains and 581 paper losses. The t -statistics test the null hypotheses that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses and paper losses result from independent decisions.

	Entire Year	June	Jul-May
PLR	0.0876	0.0400	0.0858
PGR	0.1200	0.0476	0.1166
Difference in proportions	-0.0324	-0.0076	-0.0307
t -statistic	-2.4269	-0.4036	-2.3061

Odean (1998) state that the measures of PGR and PLR are influenced by the magnitude of the portfolio. Large portfolios will consequently have smaller ratio while relatively smaller portfolios will have larger ratios. This implies that accounts with more trades have more weight than those with handful transactions. The alternative method discussed earlier, however, weights all accounts equally. Consequently, the PGR and PLR measure are slightly higher in the alternative method, particularly for value based, than those in Table 4.2.

In Table 4.2, the rate of realization given by the ratio of PGR to PLR for the entire year is approximately 1.37. This indicates that a stock that is up in price is more than 37 percent more likely to be sold on trade day than one that is down. In Odean (1998) and Weber and Camerer

(1998), they find that the ratio of PGR and PLR is 1.5. Ormos and Joo (2014) report realization rate of 1.33 among Hungarian investors.

Following Odean (1998) the study computes PGR and PLR in terms of trades and potential trades (i.e counts or number of trades). An alternative approach considers measures of PGR and PLR using volume of shares. In this method (i.e assumes independence at account level) which is adopted throughout the paper, computed gains, losses, paper gains and paper losses are aggregated across accounts prior to computing PGR and PLR. According to Odean (1998), the independence can be assumed only between accounts if PGR and PLR are calculated in this manner. The alternative test based on volume of shares (i.e the number of shares) rather than counts of trades in Table 4.3 provides an average PGR of 0.1100 and average PLR of 0.0657. The null hypothesis that the mean of PGR-PLR is less than or equal to zero is rejected with a *t*-statistic of 3.17.

Odean (1998) assumes that if investors readily realize small gains and less readily realize large losses, it is possible that they are selling similar proportions of the values of their gains and losses, though realizing gains at a higher rate on trade-counted basis. We measure gains, losses, paper gains and paper losses and compute PGR and PLR on each account using values (i.e the monetary value being product of volume of shares and share price). The average value-based PGR is 0.1413 while the average value PLR is 0.0882 (See Table 4.3). The hypothesis that the mean of PGR-PLR is less than or equal to zero is rejected with a *t*-statistic of 3.56.

Table 4.3: PGR and PLR by trades, volume and value

The table compares the combined Proportion of Gains Realized (PGR) to the combined Proportion of Losses Realized (PLR), where PGR is the trades, volume or value of realized gains divided by the sum of realized gains and trades, volume or value of paper gains, and PLR is the trades, volume or value of realized losses divided by the sum of trades, volume or value of realized losses and paper losses. The trades, volume or value of realized gains, paper gains, realized losses and paper losses are aggregated over time (2013 to 2019) and across all accounts in the data set before computing the PGR and PLR. PGR and PLR are reported for the entire year only. There are 1016.3 million shares in realized gains, 211.7 million shares in realized losses, 71.5 million shares in paper gains and 84.6 million shares in paper losses. The t -statistics test the null hypotheses that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses and paper losses result from independent decisions.

	Entire year by trades	Entire year by Volume	Entire year by Value
PLR	0.068	0.0657	0.0882
PGR	0.096	0.11	0.1413
Difference in proportions	-0.028	-0.0443	-0.0531
t -statistic	-2.67	-3.17	-3.56

Figure 4.1 charts the ratio of PGR to PLR for each month. This ratio peaks up from July to September before declining in November. It remains above 1 but fluctuates during December and April, before declining in June. It is on average above 1 during the entire year except in June. The decline over tax year is however consistent with theoretical tax loss selling. This suggests that although practical administration of the capital gains tax²⁶ for stocks held for a period less than a year, is not administered, few investors perhaps pay attention and make investment decisions accordingly. It is possible that due to weak enforcement of taxation and inconsistent policy administration, other investors expect that tax authorities may suddenly commence enforcement and so take investment decisions accordingly. It is also possible that due to inefficient tax refund system, other investors claim their losses at the end of the tax period.

²⁶ The first schedule of the Taxation Act of 2020 provides for exemption of gains from sale of shares traded on the stock exchange if those shares are held by a taxpayer for not less than twelve months.

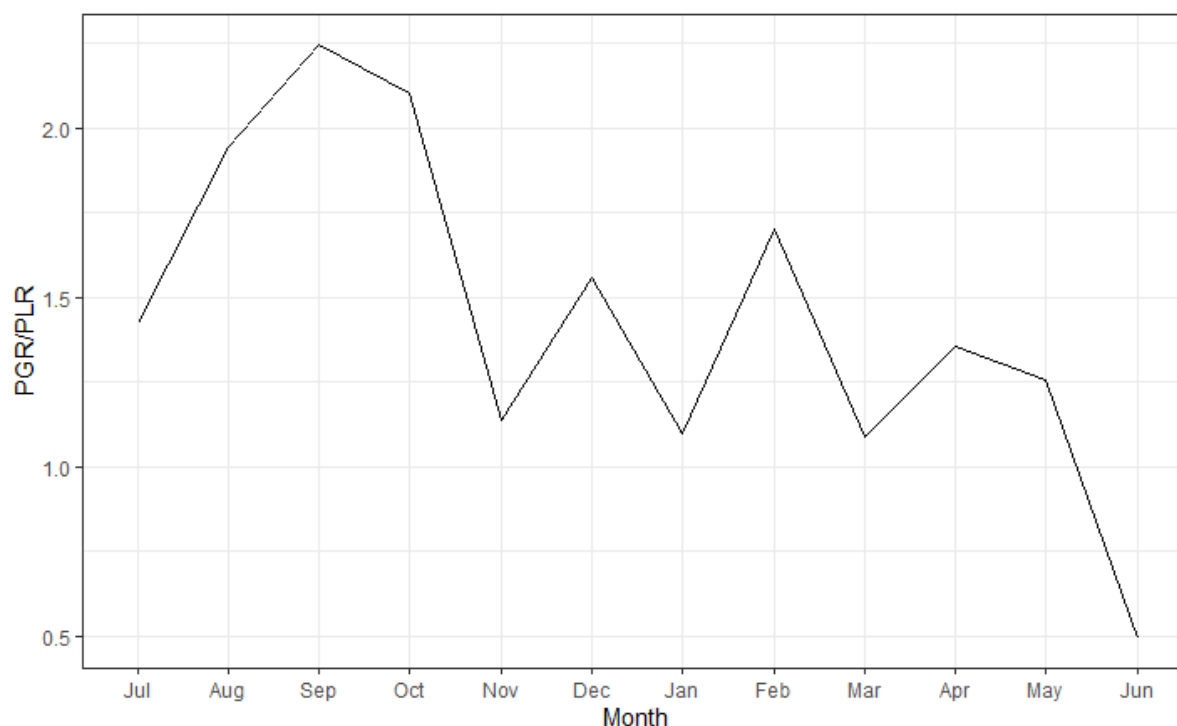


Figure 4.1: Ratio of the Proportion of Gains Realized (PGR) to the Proportion of Losses Realized (PLR) for each month. PGR is the number of realized gains divided by the sum of realized gains and paper gains. PLR is the number of realized losses divided by the sum of realized losses and paper losses.

Until the year 2010, the enabling piece of legislation for regulating capital markets in Malawi provided that stocks that held for a period over a year should be exempted from capital gains tax. This was done to promote and develop the nascent stock market as well as allowing investors take a long-term view of the market. Stocks that exchanged hands within a year of date of purchase were supposed to be subjected to capital gains tax. However, the tax authorities could not put in place a robust information system to administer the tax given the certificate system at the time. Although the stock exchange introduced an automated trading system in 2018 and linked it to the central securities depository, where change of ownership can be tracked, the tax authorities are yet to administer the tax. Consequently, investors are aware that the stock market provides this incentive of tax exemption if they take a long-term view of the market and make selling decisions accordingly.

The study follows the approach of Odean (1998) to control for influence of time periods and investor characteristics. The data set is partitioned into two equal time periods and also into two groups of traders to test the robustness of the findings.

Table 4.4 displays results when the data is partitioned equally into stocks sold from January 2013 to May 2016 and from June 2016 to October 2019. It is also partitioned into the decile of traders who trade most frequently and the nine deciles of traders who trade least frequently. In the data set, the most active 10 percent account for 74.3 percent of total trades (volume).

During the time period 2013 to 2016, investors realize more gains than losses for the entire year. This is also the case during the second partition of the sample although the rate at which they realize gains than losses declines. In Table 4.4, the rate of realization, i.e. ratio of proportion of gains to proportion of losses for the entire year, declines from 2.28 during 2013 to 2016 period to 1.51 during 2016 to 2019 period. This finding is also consistent with the study of Barber *et al.*, (2007) which argues that disposition effect declines in period of market appreciation. Investors who trade less frequently trade, also realize more gains than losses in the entire year than frequent traders. Odean (1998) suggest that due to how the portfolios are reconstructed over time, the average portfolio size in the later part of the time period are smaller just like they are smaller for frequent traders. Consequently, PGR and PLR are relatively large. The ratio of PGR/PLR during the periods indicates that there were more sell-offs in the first time period than in the second. It is also possible that as time passes the Malawi investors learn to overcome disposition bias, consistent with the findings of Muhl and Talpsepp (2018).

Table 4.4: Comparison of the aggregate Proportion of gains Realized (PGR) to the aggregate Proportion of Losses Realized (PLR)

The table compares the aggregate Proportion of gains Realized (PGR) to the aggregate Proportion of Losses Realized (PLR), when PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains, and PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. The data are portioned into the period Jan 2013- May 2016 and June 2016- Oct 2019 and into the 10 percent of the accounts that actively trade and the 90 percent that trade least regularly. There are there are 758 realized gains, 630 realized losses, 8942 paper gains and 8574 paper losses for the period 2013-2016. For 2016-2019, there are 1246 realized gains, 846 realized losses, 13119 paper gains, and 12438 paper losses. For active traders there are 244 realized gains, 110 realized losses, 1798 paper gains and 1246 paper losses. For less regular traders, there are 1730 realized gains, 1439 realized losses, 20215 paper gains, and 19810 paper losses. The t-statistics test the null hypotheses that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses and paper losses result from independent decisions.

	2013-2016	2016-2019	Regular Investors	Less Investors	regular
Entire year PLR	0.0566	0.0677	0.1178		0.0779
Entire year PGR	0.1290	0.1021	0.1566		0.1149
Difference in proportions	-0.0725	-0.0344	-0.0388		-0.0370
<i>t</i> -statistic	-3.0397	-2.2001	-0.9388		-2.6928
June PLR	0.0634	0.0972	0.2400		0.0751
June PGR	0.0738	0.0756	0.4800		0.0967
Difference in proportions	-0.0104	0.0216	-0.2400		-0.0216
<i>t</i> -statistic	-0.2815	0.4334	-0.8090		-0.3632
Jul-May PLR	0.0668	0.0649	0.0899		0.0822
Jul-May PGR	0.1371	0.1086	0.1464		0.1136
Difference in proportions	-0.0703	-0.0437	-0.0565		-0.0314
<i>t</i> -statistic	-2.6668	-2.6483	-1.5412		-2.1813

One of the rational explanation for disposition effect in literature is claims by the study of Lakonishok and Smidt (1986) that disposition effect is motivated by rebalancing of investors' portfolios. Odean (1998) challenges this claim by arguing that investors need not dispose of an entire portfolio if they trade for rebalancing. By controlling for partial sales, Odean (1998) finds that investors continue to realize more gains than losses however realize losses in a tax

period at a higher rate than gains. The findings by the study suggests that investors selling behavior is not motivated by rebalancing of portfolio.

This study tests for portfolio rebalancing. If we control for rebalancing then we do not expect to find support for disposition effect, in support of rational explanation. The PGR and PLR are computed using only sales that are of an account's entire portfolio in a stock (and using paper gains and losses on the days of those sales, in line with Odean (1998). There are few observations of this kind. The results are presented in Table 4.5.

In Table 4.5, for the whole year investors appear to sell winners more than losers. In June the trend slightly reverses. However the results are not statistically significant. This means that after controlling for partial sales, there is no support for the assertion that investors realize more gains than losses during the entire year. This result contradicts the findings of Odean (1998) on the test of portfolio rebalancing. In the tax period, there is no significant difference between losses that are realized from gains.

Table 4.5: PGR and PLR when the entire position in a stock is sold

The table compares the aggregate Proportion of gains Realized (PGR) to the aggregate Proportion of Losses Realized (PLR), when PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains, and PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. The losses and gains are counted only if the portfolio's total position in another stock held in the portfolio was sold that date. Realized gains, paper gains, realized losses, and paper losses are aggregated over time (2013 to 2019) and across all accounts in the data set. PGR and PLR are reported for the whole year and for June only. For the whole year, there are 839 gains, 9039 paper gains, 867 realized losses and 12386 paper losses. For June there are 240 realized gains, 2138 paper gains, 327 realized losses and 3677 paper losses. The *t*-statistics test the null hypotheses that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses and paper losses result from independent decisions.

	Whole year	June
PLR	0.0522	0.0428
PGR	0.0874	0.0402
Difference in proportions	-0.0352	0.0026
<i>t</i> -statistics	-1.1478	0.0816

It has also been argued by Odean (1998) that investors who exhibit disposition effect motivated by portfolio rebalancing are likely to make new purchases. Thus, it is expected that if investor exhibit disposition effect, then they will make new purchases as they exercise portfolio rebalancing. Thus the study tests for portfolio rebalancing while controlling for new purchases. Like in Odean (1998), this study computes PGR and PLR using only sales for which there are no acquisition on the following 21 days and using paper gains and paper losses on the day of those sales. The results are presented in Table 4.6.

Table 4.6 shows that after removing sales that are influenced by rebalancing, investors dispose winners more readily than losers in the entire year. There is thus evidence to support the assertion that disposition effect is not motivated by portfolio rebalancing, consistent with the findings of Odean (1998). The tax effect for June however is not significant.

Table 4.6: PGR and PLR when no new stock is purchased within 21 days of sale

The table compares the aggregate Proportion of gains Realized (PGR) to the aggregate Proportion of Losses Realized (PLR), when PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains, and PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. In this table losses and gains are counted only if a no new purchase was made into a portfolio on the day of the sale or within three weeks following sale. Paper (unrealized) gains and losses are counted for days on which qualifying sales were made. Realized gains, paper gains, losses and paper losses are aggregated over time (2013 to 2019) and across all accounts in the data set. PGR and PLR are reported for the entire year and for June only. For the entire year, there are 2452 realized gains, 20881 paper gains, 1663 realized losses and 20739 paper losses. For June there are 97 realized gains, 728 paper gains, 43 realized losses and 526 paper losses. The t-statistics test the null hypotheses that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses and paper losses result from independent decisions.

	Whole Year	June
PLR	0.0666	0.0400
PGR	0.1312	0.0473
Difference in proportions	-0.0646	-0.0073
t-statistic	-5.4713	-0.0396

Literature suggests that investors might sell winners and hold losers because of the belief in mean reverting price [(Odean (1998))]. The study tests justification of this belief, *ex post*. It computes excess returns for two investment horizons following the sale of a winning stock or observation of a paper loss. The returns are calculated in excess of the Malawi All Share Index (MASI) value weighted index. The purpose of the test is to ascertain if investors realize gains early to avoid price falls because of the belief that today's gainers will be tomorrow's losers. It is expected that the evidence will support the assertion of the mean reversion belief.

Table 4.7 reports excess returns for periods following the sale of a winning stock or the observation of a paper loss. The study considers one-year and two-year investment horizons following the study of Odean (1998). A one-year investment horizon is an estimate of average investor's investment horizon. It represents 252 trading days in a year. On the other hand, the two-year investment horizon reflects 504 trading days in finance literature. The returns are calculated in excess of the Malawi All Share Index (MASI) value weighted index. The data shows that for winners that are sold, the average excess return over the following year is 4.8 percent less than it is for losers that are not sold. It is however not significant. For a two-year investment horizon, the return is 9.4 percent less for winners sold than for losers. This is however significant. This means that over a two -year investment horizon, the Malawian investors behavior appear consistent with Kaustia (2010) study's assertion that that investors who believe in mean reversion would exhibit reverse disposition effect for stocks with paper gains (or losses) and bad (or good) recent performance. It therefore implies that the Malawian investors do not exhibit inefficient behavior over a two -year investment horizon. This result varies significantly from the findings of Odean (1998) who find that average excess return for winners over the following year to be 3.4 percent more than it is for losers. The result also contradicts the finding of Jegadeesh and Titman (1993) that stocks have momentum.

Table 4.7 : Ex post returns

This table compares average returns in excess of the Malawi All Share Index (MASI) value weighted index to stocks that are sold for a profit (winning stocks sold) and to stocks that could be, but are not, sold for a loss (paper losses). Returns are measured over 252 and 504 trading days subsequent to the sale of realized winner and subsequent to days on which sales of other stocks take place in the portfolio of a paper loser. *p-value* refer to the frequency with which differences in excess returns over the period in the empirical (bootstrapped) distribution exceed the difference in excess returns observed in the data.

	Performance over next 252 Trading Days	Performance over next 504 Trading Days
Average excess return on winning stocks sold	-0.0205	0.0232
Average excess return on paper losses	0.0276	0.1173
Difference in excess returns	-0.0481	-0.0941
<i>(p-value)</i>	0.1175	0.0235

It has also been argued by Odean (1998) that selling behavior is influenced by trading costs. Odean (1998) examines whether trading costs for both winners and losers affect selling decisions. The study finds that when winners and losers of similar magnitude are compared, investors still prefer to sell winners and hold onto losers. The study tests the hypothesis that losses are realized more slowly due to the higher transaction costs.

Table 4.8 reports PGR and PLR for different price ranges and return ranges for July through May. The observations have been generally equally distributed. Stocks with a price less than or equal to K13.00, with prices greater than K13.00 but less than K64.00, and prices greater than K64.00 represent 33.47 percent, 33.85 percent and 32.68 percent respectively of the data set. Odean (1998) suggests that in order to control for variation of return values of large losers in the lower price range and of large winners in the upper price range, the returns ought to be partitioned based on absolute magnitude. The ranges for absolute values of returns are: 0 to 0.15, 0.15 to 0.30, 0.30 to 0.50 and greater than 0.50.

The study finds that none of the partitions suggest that winners are realized at a higher rate than losers. The difference is not statistically significant. Thus, we fail to reject the hypothesis that

losses are slowly realized due to high transaction costs. This means that there is no support for the assertion that transaction costs influence selling decisions.

Table 4.8: PGR and PLR portioned by Price and Return

The table compares the aggregate Proportion of Gains Realized (PGR) to the aggregate Proportion of Losses Realized (PLR) where PGR is the number of realized gains divided by the number of realized gains plus the number of paper gains, and PLR is the number of realized losses divided by the number of realized losses plus the number of paper losses. The data are partitioned on stock price and on absolute value of the return to date (R), for all accounts 2013 to 2019, July through May only. The t-statistics test tests the null hypothesis that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses, and paper losses result from independent decisions.

	$ R \leq 0.15$	$0.15 < R \leq 0.30$	$0.30 < R \leq 0.50$	$0.50 < R $
Price $\leq$ K13				
PLR	0.1629	0.1653	0.0968	0.1130
PGR	0.1073	0.1519	0.1047	0.1452
Difference	0.0556	0.0134	-0.0079	-0.0322
t-statistic	1.0139	0.1727	-0.1234	-0.6415
K13 < Price $\leq$ K64				
PLR	0.0833	0.1331	0.2030	0.0855
PGR	0.1329	0.0674	0.1679	0.0873
Difference	-0.0496	0.0657	0.0352	-0.0018
t-statistic	-0.9899	1.6444	0.3365	-0.0629
K64 $\leq$ Price				
PLR	0.0714	0.1355	0.1771	0.1751
PGR	0.0928	0.0834	0.0787	0.2886
Difference	-0.0214	0.0521	0.0984	-0.1135
t-statistic	-0.8728	0.6905	1.4661	-0.9263

Research studies such as Grinblatt and Keloharju (2001), Choe and Eom (2009), and Shapira and Venezia (2001) document presence of disposition bias amongst individual investors while other studies such as Coval and Shumway (2005) and Chen *et al.*, (2007) document that institutional investors are less prone to the disposition bias. We partition our sample between retail investors and institutional investors during the sample period.

Table 4.9 reports PGR and PLR for investor types, namely retail and institutional investors during the entire sample. The table shows that retail investors exhibit the tendency to sell winners disproportionately than losers compared to institutional investors. The difference is statistically significant. This finding is consistent with the studies such as Shapira and Venezia (2001), Feng and Seasholes, (2005), Dhar and Zhu (2006) and Choe and Eom (2009). For example, Choe and Eom (2009) documents that retail investors are more prone to disposition bias relative to institutional investors and foreigners in Korean futures market. The lack of disposition among institutional investor is also consistent with findings such as Coval and Shumway (2005) and Chen *et al.*, (2007) who document that institutional investors are less frequently exposed to disposition bias. The finding therefore suggests that the Malawian institutional investors have information while those prone to disposition effect lack information consistent with assertions by Shapira and Venezia (2001).

Table 4.9: PGR and PLR by investor type

The table compares the aggregate Proportion of Gains Realized (PGR) to the aggregate Proportion of Losses Realized (PLR) where PGR is the number of realized gains divided by the number of realized gains plus the number of paper gains, and PLR is the number of realized losses divided by the number of realized losses plus the number of paper losses. The data are partitioned by investor type: retail investors and institutional investors, for all accounts 2013 to 2019. The t-statistics test tests the null hypothesis that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses, and paper losses result from independent decisions.

	Total	Retail Investors	Institutional Investors
PLR	0.0876	0.0944	0.0541
PGR	0.1145	0.1274	0.0514
Difference in proportions	0.0269	0.033	-0.0027
t-statistic	2.0618	2.1449	-0.1976

4.7 Discussion

The study investigates the behavior of investors in Malawi market. Specifically, it tests for presence of disposition effect in a least developed country. It analyzes transactions records of

investors. It tests the hypothesis that investors sell of winning stocks more readily than stocks whose prices have declined.

The primary finding is that Malawian investors sell winning stocks more readily than losing stocks in aggregate assuming independence at a transactional level as well as at account level. The effect however declines over subperiods. A test of rebalancing shows that after removing sales that may be influenced by rebalancing, the data indicates that there is evidence of disposition effect for the entire year. In a related test where partial sales are controlled for rebalancing, the study does not find significant results. A test of mean reverting prices shows that investors who sell winners do not lose out, however the results are not significant over a year. The study does not find any evidence that selling decisions are influenced by transaction costs. Hence the robustness test results are mixed.

The most interesting finding is that our results contrast the evidence documented by Grinblatt and Han (2002) that disposition effect generates price momentum. The evidence in this study suggests that this is not the case with Malawian investors. Hur, Pritiman and Sharma (2010) document that disposition effect emanates from individuals who trade actively and can possibly generate price momentum. The investors in this study do not actively trade compared to previous studies such as Odean (1998) and Grinblatt and Han (2005), and so fall far short of creating momentum. Hence, the inability to generate momentum is consistent with the findings of Barber *et al.*, (2007).

It is likely that while the entire period show evidence of disposition effect, there are time periods when it is pronounced and when it is not. It is likely that it wanes as prices rise. Barber *et al.*, (2007) argue that disposition effect declines in periods of market boom. This is evident in the later half of the study period. Given that individual traders generally less frequently trade, such lack of frequent trading impairs the presence of the disposition bias from individuals. It is also possible that with experience and overtime, as individual investor gain experience, they overcome the behavioral bias and so the effect wanes overtime. Studies such as Feng and Seasholes (2005), Grinblatt and Keloharju (2001), Seru, Shumway and Stoffman (2010) Shapira and Venezia (2001) document that learning minimises disposition bias.

The rate at which Malawi investors realize winners than losers is lower than the study of Odean (1998), Weber and Camerer (1998) at 1.5 and Chen *et al.*, (2007) at 1.67, however it is marginally higher than Hungarian investors at 1.33 [(Ormos and Joo (2014)]. Barberis and Xiong (2009) and Hens and Vlcek (2011) argue that prospect theory supports disposition effect

but it does not always hold. In a test where partial sales are controlled for rebalancing, the study does not find support for the assertion that investors realize more gains than losses during the entire year. The reason could possibly be that there were very few trades that are executed within 21 days. Therefore, the study has very few observations to derive results that could reflect disposition effect consistent with findings in literature such as Odean (1998).

It is likely the magnitude of the portfolio as well as number of transactions in the study are relatively smaller compared to those obtaining in developed markets. Odean (1998) and Da Costa, *et al.*, (2013) explain that disposition effect is influenced by portfolio size and trading frequency. Malawi like many other least developed countries are characterized by few trades and low liquidity, in some cases nil trades in a whole trading session.

A test for mean reverting prices suggests some evidence of price reversal over a two-year period. However, it is not entirely consistent with the findings of DeBondt and Thaler (1985, 1987) who document price reversal over longer horizons of three to five years. Bashall, Willows and West (2018) document that short-term reversion is not a significant factor in influencing investor to exhibit disposition effect. Our results show that investors who cash in on winning stocks more readily than losers may do so following this belief given the shallowness of the market. This is probably because price movements are so volatile and dramatically move off the fundamentals led by a few trades (Samuels *et al.*, 1981). Thus, there is irrational decision making regardless of the fundamentals. It could also be that due to inconsistent economic policy reversals that may affect future returns, investors are typically risk averse. In developed markets, price movements are largely driven by news or fundamentals and given that there are more institutional traders, it is rare for prices to move dramatically without raising eyebrows. Singh (1991) documents that LDC's are characterized by volatility (where prices vary more than economic variables), suggesting that they are less meaningful in allocative role. Volatility also discourages risk averse investors as well as raising the cost of capital.

The findings of this study may be helpful to the regulators to recognize that rational investors may exploit investors who suffer from disposition bias and build better portfolios. Dhar and Zhu (2006) documents that experiences investors have potential to make money from the irrational investment decisions of the less sophisticated investors. Thus, this irrational behavior could be exploited.

The findings may also be of significance to financial institutions which may render advice to investors who are likely to be negatively affected by disposition effect. Studies such as Weber and Camerer (1998), Grinblatt and Keloharju (2001), Shapira and Venezia (2001), Feng and Seasholes (2005), Boolell-Gunesh *et al.*, (2009), Seru, Shumway and Stoffman (2010) and Muhl and Talpsepp (2018) document that learning minimises disposition effect, such that individuals who trade actively may gain experience and overcome behavioral bias. This is important for LDCs as its investors are typically less sophisticated and so need to build expertise by frequent trading and learning experience. Investors may also be taught to adopt hedonic framing, a mental approach can be utilized to minimize disposition effect [(Wierzbicki and Seidens (2018))].

4.8 Conclusion

Recent finance research has shown that investment behavior conflicts with the assumptions of rationality and at times observed to be inconsistent with models of standard finance theory. One such behavior is termed disposition effect, the tendency to sell winning stocks quickly than losing stocks. This behavior has been well documented in developed economies to be costly for investors. Researchers debate about the potential causes of this behavior. Portfolio rebalancing and transaction costs have been argued as some of the rational explanations for justifying exhibition of disposition effect. However, these are debatable in literature.

The purpose of this paper was to investigate the extent of the prevalence of disposition effect among investors in a least developed country and explain potential causes. We study disposition effect because it matters for academicians, investors and policy makers. For example, it has been argued that disposition effect leads to momentum trading (Jegadeesh and Titman (1993), Rouwenhorst, (1998) and Grinblatt and Han (2005)). It has also been documented that investors can exploit patterns and build better portfolios (Heath, Huddart and Lang (1999)). In addition, studies such as Dhar and Zhu (2006) claim that rational investors can make money off irrational investors.

The model of disposition effect predicts that investors realize more gains relative to the number of gains available for realization and realize fewer of the losses relative to number of losses available. Specifically, the study adopts Odean (1998) measure to calculate realized gains and realized losses for each investor and then aggregate over all investors and trading days for the entire sample period from 2013 to 2019. Then we set up proportions namely Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR). We then compare the differences between PGR and PLR. The difference between the average PGR and PLR for each

category is tested for statistical significance using a one tailed test. A significant difference suggests that on average investors are willing to realise one element over another.

The primary finding is that investors sell winning stocks more readily than losing stocks. The disposition effect appears to decline over time. Although Malawian investors exhibit disposition effect, this does not translate into momentum trading. This finding is consistent with the study of Barber *et al.*, (2007). Our findings shows that a test of rebalancing indicates that there is evidence of disposition effect. In a related test where partial sales are controlled for rebalancing, the study does not find significant results. The study does not find any evidence that selling decisions are influenced by transaction costs.

It is envisaged that policy makers may find the results of the study useful. In Malawi, like many other least developed countries, financial regulators champion financial sector development programs to promote and attract long term savers into the financial market. Thus, they can build regulatory systems to monitor that less sophisticated investors are not exploited by requiring amongst others deployment of some sophistication e.g. stop loss orders. In addition, financial institutions which render financial advice to investors may package investor awareness messages and/or put in place systems to help less sophisticated investors avoid costly selling decisions by developing strategies that may overcome the behavior bias.

The findings of the study document evidence from a least developed country about the prevalence of disposition effect in stock market, consistent with the findings of Odean (1998), Shapira and Venezia (2001), Barber *et al.*, (2007) in developed markets. The most interesting finding is that our results contrast the evidence documented by Grinblatt and Han (2005) that disposition effect generates price momentum.

5.0 Do Malawian institutional investors engage in herd behavior?

5.1 Introduction

Institutional investors play a key role in the financial system through ownership and trading of securities (Choi and Sias 2009). Studies such as Grinblatt and Keloharju (2000) suggest that relative to individuals, institutional investors possess resources and special capabilities to make rational investment decisions and possibly contribute to informational efficiency of the markets. Thus, given their importance, institutional trading behavior is of interest to academicians, traders and policy makers.

A number of empirical studies have investigated the behavior of institutional trading and its impact on asset prices and returns. For example, studies such as Lakonishok, Shleifer and Vishny (1992); Grinblatt, Titman and Wermers (1995); Nofsinger and Sias (1999); Wermers (1999); Sias, Starks and Titman (2006) suggest that institutional investors follow other institutional investors i.e. they herd over time. Gavriilidis and Kallinterakis (2021) state that herd behavior is a trading pattern in financial markets. It has been documented in various market settings at single market setting (Sias 2004) and at industry level (Choi and Sias 2009).

There are several reasons why herd behavior is important in financial markets to warrant an investigation. From a policy perspective, correlated patterns of trades have been documented to weaken financial stability as reported by Demirer and Kutan (2006). Economou, Kostakis and Philippas (2011) state that an increase in the level of herding among specific assets minimises the benefits of portfolio diversification. Devenow and Welch (1996) argues that mispricing may result from herd tendencies and potentially impair the price discovery process leading to undermining the principles of market efficiency. Besides, Economou, Kostakis and Philippas (2011) suggests that mispricing may lead to sub optimal decision making by institutional investors and corporations as well as inaccurate policy response from regulatory authorities.

In addition, understanding herd behavior has practical implications for policy makers. Researchers such as Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) state that understanding herd behavior is part of market discipline and a policy response may be effectively crafted to deal with the cause. Gavriilidis, Kallinterakis and Ferreira (2013a) suggest that awareness of herding may signal to regulators that a section of fund managers lack either information or skills or choose not to utilise them by copying peer's actions. They state that

this has implications for portfolio diversification which may harm investors; and if the practice is so prevalent can potentially be price destabilizing.

Studies such as Gavriilidis, Kallinterakis and Ferreira (2013a) and Economou, Gavriilidis, Kallinterakis, and Yordanov (2015) have investigated the prevalence and sources of herding by institutional investors. They argue that herding is prevalent where there are less efficient regulatory frameworks. These studies focus on developed markets. There is dearth of literature in least developed countries where the regulatory systems are not only rudimentary but also inefficient implying that the quality of information upon which investors ought to base investment decisions is low.

We investigate institutional herding in Malawian context where there are 122 institutional traders during the period of study from January 2007 to October 2019. They actively trade in the stock market and comprise of over 74 percent of market activity. Herding has been documented in literature in market environment where there are information asymmetries, weak regulatory systems and low trading volumes, which coincidentally characterise least developed countries (LDCs). Such market provides a conducive environment for institutional investors to herd and engage in exploitative behavior. For example, Hirshleifer and Hong Teoh (2003) state that presence of herding provides an opportunity for hedge fund and mutual fund managers to exploit the herd behavior of irrational investors. In addition, LDCs are characterized by poor institutional frameworks with inadequate enforcement mechanisms, low transparency levels and lack of competition. The trading environment is thus theoretically conducive for herd behavior. We thus envision to find evidence of herding within the Malawian market.

There is a lot of debate about the price impacts and explanation of institutional herding. A lot of studies such as Gutierrez and Kelley (2007), Puckett and Yan (2008), Dasgupta, Prat and Verardo (2011a) and Brown, Wei and Wermers (2014) have argued that herd behavior is destabilizing and increases volatility as well as contributes to inefficient markets. On the other hand, it has been argued that through its speeding of incorporation of new information into prices, it has a stabilizing effect and contributes to efficient market. There is a lot of theoretical studies that have argued that herding moves prices towards their intrinsic values such as Bikhchandani, Hirshleifer and Welch (1992); Froot, Scharfstein and Stein (1992); Hirshleifer, Subrahmanyam and Titman (1994); Wermers (1999) with empirical support documented by studies such as Nofsinger and Sias (1999), Wermers (1999), Sias (2004) and Choi and Sias

(2009). This remains a debate in literature. We envisage to contribute to the existing body of literature by investigating the existence and effects of institutional herding using trading data in the context of Malawi, a least developed market. Using the methodology of Sias (2004), we envisage to get a better understanding of extent and source of herd behavior in a market environments where regulatory frameworks are crude.

5.2 Data and Methodology

5.2.1 Data

We use unique data to extend herding effects tests to provide further insight into motivation that drives herd behavior from the context of Malawi. The data comprise of ownership by institutional investors taken from the central bank²⁷. The sample comprises of 122 institutional investors. They invest in 16 stocks during the sample period. The data are classified into 7 institutional investor types; namely brokers, pension funds; fund managers; insurance companies, banks, other financial institutions and non-financial entities. The data set provides information on the ticker, code for the institution, type of investor, the volume of shares under each ticker. The data spans from January 2007 to October 2019. It has been aggregated into quarter dates and covers 52 quarters.

Table 5.1 provides some descriptive statistics regarding institutional investors holdings during the sample period. The table shows that the average number of stocks traded during the sample period by at least one institutional investor was 8.5 while the average number of stocks traded by at least two institutional investors was 5.7. The average number of securities held by each institutional investor was 8.5. These figures suggest a small market compared to the study of Sias (2004), where herding may be facilitated by high concentration with few funds trading in each stock during the quarter.

²⁷ The central bank is also the regulator of securities market.

Table 5.1: Descriptive statistics

Each quarter between January 2007 and October 2019 we calculate the number of institutional investors (overall and by type), the number of securities traded by at least 1 and 2 institutional investors, the number of securities traded by at least each investor type and the cross-sectional average of securities held by each institutional investors (overall and by investor type). Panels A, B and C report the time series averages of these figures as well as their values over 5-year periods.

	All sample	2007-2010	2011-2015	2016-2020
No of Unique Institutions	122	60	83	78

Panel A

Type of Institutions	Average all periods	2007-2010	2011-2015	2016-2020
Brokers	4.0	5	4	5
Pension Funds	14.2	14	17	25
Fund managers	4.6	4	7	6
Insurance Co	6.4	8	14	12
Banks	4.8	9	7	4
Other FI's	8.9	13	23	19
Non-Financial Inst	5.4	7	11	7

Panel B: Average number of securities with:

>= 1 trader	8.5031	8.2423	8.6495	8.4721
>=2 traders	5.6636	4.1682	6.1333	6.4709

Panel C: Average number of securities held by each institutional investor

All institutions	8.5031	8.2423	8.6495	8.4721
Brokers	8.4214	8.5146	8.5189	8.2693
Pension Funds	8.7120	8.2336	9.1753	8.5952
Fund managers	8.5436	7.9237	8.815	8.4565
Insurance Co	8.6224	8.935	7.989	8.8146
Banks	8.0659	7.7387	7.7823	10.6667
Other FI's	8.6739	9.200	8.8247	8.1807
Non Financial Inst	8.4488	6.9591	10.0794	7.5455

5.2.2 Methodology

Like in Sias (2004), we calculate for every quarter, each institutional investor's position in each security as a fraction of the security's shares outstanding. An institutional investor is considered a buyer if for each security and quarter their ownership in the stock increases; seller if it decreases or it is not classified as either of these if does not change. For each stock-quarter, we compute the proportion of institutional investors trading the security that are buyers. Sias

(2004) defines the temporal dependence of institutional demand as the raw fraction of institutions buying security k during quarter t :

$$Raw\Delta_{k,t} = \frac{No\ of\ institutions\ buying_{k,t}}{No\ of\ institutions\ buying_{k,t} + No\ of\ Institutions\ selling_{k,t}} \dots\dots\dots (1)$$

In order to be considered for analysis, a security must have been traded by at least one institutional investor so that the denominator is greater than equal to zero.

5.3 Tests for Institutional herding

Sias (2004) state that the tests for herding implicitly or explicitly examine the temporal patterns in the cross section of institutional trades i.e. whether they follow each other's trades. This approach is a direct measure of cross-sectional temporal dependence as it measures the extent to which trades follow each other over adjacent quarters. Sias (2004) argues that if institutional investors follow each other into and out of the same securities or if institutional investors follow their own previous-quarter trades, then the fraction of institutions buying in the current quarter will be positively correlated with the fraction of institutions buying in the previous quarter.

As in Sias (2004), we standardize both the dependent and independent variables in order to provide for aggregation over time and to directly compare coefficients across different measures of institutional demand and investor types so that both have zero mean and unit variance. The standardized fraction of institutions buying security k in quarter t (denoted $\Delta_{k,t}$) is denoted as;

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})} \dots\dots\dots (2)$$

Where $\overline{Raw\Delta_t}$ is the cross-sectional average (across K securities) raw fraction of institutions buying in quarter t and $\sigma(Raw\Delta_{k,t})$ is the cross-sectional standard deviation (across K securities) of the raw fraction of institutions buying in quarter t . It should be noted that since standardization is merely linear scaling, the correlations between the variables and the R^2 s associated with the regressions are not affected. In order to test for the temporal dependence of institutional demand, we follow an econometric assumption by Sias (2004) that the

standardized raw fraction $\Delta_{k,t}$ follows an autoregressive process of order one. In other words, the institutional demand follows an autoregressive process of order one :

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \quad (3)$$

Gavriilidis, Kallinterakis and Ferreira (2013a) explain that the first order autocorrelation coefficient (β_t), i.e. the slope, represents institutional demand's cross-sectional correlation between quarter t and quarter $t-1$ since both sides of Eq (3) are standardized and there is only one independent variable ($\Delta_{k,t-1}$) on the right hand side of the equation. Sias (2004) breaks down β_t into components that are due to momentum and another one due herding. More specifically, β_t is decomposed as follows:

$$\begin{aligned} \beta_t &= \rho(\Delta_{k,t}, \Delta_{k,t-1}) \\ &= \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \\ &\quad \times \sum_{k=1}^K \left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}} \right] \\ &\quad + \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \\ &\quad \times \sum_{k=1}^K \left[\sum_{n=1}^{N_{k,t}} \sum_{m=1, m \neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}} \right], \quad \text{-----}(4) \end{aligned}$$

where $N_{k,t}$ is the number of institutional investors actively trading security k in quarter t . $D_{n,k,t}$ is dummy variable taking the value of one when institutional investor n is a buyer of security k in quarter t and zero when institutional investor n is a seller of security k in quarter t . $N_{k,t-1}$ is the number of institutional investors actively trading security k in quarter $t-1$. $D_{n,k,t-1}$ is a dummy variable equal to one when institutional investor n is a buyer of security k in quarter $t-1$ and zero when institutional investor n is a seller of security k in quarter $t-1$. $D_{m,k,t-1}$ is a dummy

variable that equals one when institutional investor m ($m \neq n$) is a buyer of security k in quarter $t-1$ and zero when institutional investor m ($m \neq n$) is a seller of security k in quarter $t-1$.

The first term on the right-hand side of the above equation (Eq 4) is the portion of the correlation due to institutional investors following their own trades. If it is positive (negative), then institutional investors tend to follow (reverse) their trades over adjacent quarters. The second term on the right-hand side of the above equation (Eq4) is the portion of the correlation due to herding i.e. institutional investors following the trades of other institutional investors. If it is positive (negative), then institutional investors tend to follow (trade against) each other over adjacent quarters.

We estimate both equations (3) and (4) for the entire sample. The indices data are obtained from Malawi Stock Exchange (MSE) and Reserve Bank of Malawi and confirmed by Thomson Reuters-DataStream. In order to ascertain the existence of institutional herding we adopt the methodology of Sias (2004). This approach has been used amongst others by Gavrilidis, Kallinterakis and Ferreira (2013a,b) and Holmes, Kallinterakis and Ferreira (2013). The methodology also examines intent of herding through the interaction of institutional herding with different states of the trading environment. Youssef (2022) state that market microstructure factors such as returns, volume and volatility drive herd behavior. Therefore, we examine intent of herding through the interaction of institutional herding with different states of the trading environment.

5.3.1 Test for market returns

Researchers document herd behavior in both down and up markets. Studies such as Economou, Kostakis and Philippas (2011), Holmes, Kallinterakis and Ferreira (2013) and Yao, Ma and He (2014) document empirical evidence that herd behavior is prevalent during down- markets due to investors' risk aversion, while other studies such as Arjoon and Bhatnagar (2017) document more pronounced herd behavior in up-market on Trinidad and Tobago Stock Exchange. In addition, there is potential herd behavior among poor performing managers because institutional investor performance assessment suggests this to be the case (Scharfstein and Stein 1990). Low abled managers tend to hide their performance by copying the actions of good performing managers. This is likely prevalent during declining trading periods when investors are likely to record losses and so face performance assessment issues. Given that declining market conditions lead to overall loss conditions in the market, herding on the trades of good managers is a better argument for low abled managers as they have a reason to claim that they

made good decision like others except that the entire market registered losses, and so can share the blame. The herding behavior makes it challenging for investors to make proper assessment to distinguish between low-abled and high-abled managers as well as obscuring the low capability of poorly abled managers. Stavroyiannis and Babalos (2019) state that herding behavior exists during negative returns.

Ballis and Drakos (2020) state that herding is present during rising market returns. Rising market conditions prompt low abled managers to intentionally mimic the actions of high-abled managers since underperformance during these market conditions can be easily noticed, assessed and attributed to low abilities. If institutional herding is intentional, then we would expect a relationship between market/sector returns and institutional herding i.e. institutional herding would exhibit differences between declining and rising market conditions. If institutional investors herd spuriously, then no such differences would be expected to arise. More formally, we test the following hypotheses:

H₁: Institutional herding depends on market returns.

H₂: Institutional herding does not depend on market returns.

We adopt the approach by Gavriilidis, Kallinterakis and Ferreira (2013a), to test for the effect of market returns over institutional herding, by using quarter end closing prices of Malawi All Share Index (MASI) for the period January 2007 to October 2019. We then calculate their quarterly log-differenced returns and rank the return series of the index in ascending order. Then we split the return series into two parts, based on whether a quarter's returns are positive or negative (i.e. whether the market index has risen or declined in quarter t compared to quarter $t-1$). We then split β_I and its two components (i.e. momentum and herding) of each part accordingly.

5.3.2 Test for Market volatility

Tan *et al.* (2008) study suggests that investors engage in herd behavior during high volatile period due to increased uncertainty and risk. Gavriilidis, Kallinterakis and Ferreira (2013a) suggest that highly volatile trading environment is associated with high informed trading since high flow of information leads to price volatility as the market incorporates the information into prices. The authors explain that a highly informative environment discourages herd behavior because there is available information on which investors can base trades on. From the perspective of low-abled managers, such an environment provides complexity and challenges for investment decision making, since they lack necessary skills hence leads to herd

behavior. In calmer periods however, low abled managers easily imitate the trades of highly abled managers because such an environment allows easy visibility of each other's trades. However, other studies such as Economou, Kostakis and Philippas (2011), Holmes, Kallinterakis and Ferreira (2013), Guney, Kallinterakis and Komba (2017) and Kallinterakis and Wang (2019) document herd behavior in low volatility environment.

If institutional investors herd intentionally, we expect an association between market volatility and herd behavior (i.e. institutional behavior would exhibit differences between volatile and calmer periods). On the other hand, if institutional investors do not intentionally herd, then we would not expect any differences. Put differently, the quarterly variations in market volatility would not be expected to generate variations in homogeneity among institutional investors.

More formally, our hypotheses are as follows:

H₁: Institutional herding depends on market volatility.

H₂: Institutional herding does not depend on market volatility.

We test for the effect of market volatility over institutional herding by utilising daily closing prices of the Malawi Stock Exchange Index for the period January 2007 to October 2019. We calculate the volatility of the index every quarter using the approach by Schwert (1989). The technique was also adopted by Gavriilidis, Kallinterakis and Ferreira (2013a). The approach calculates volatility as the quarterly standard deviation of quarterly log differenced returns for the entire Malawi All share index. We then rank the quarterly volatility observations in ascending order. We then split the volatility series in two portions, high and low depending on values being above or below the median value. We then split β_I and its two components according to each portion.

5.3.3 Tests for Market volume

Youssef (2022) suggests that trading volume enhances herd behavior. Empirical evidence is documented by Tan *et al.* (2008) and Gavriilidis, Kallinterakis and Ferreira (2013a). For example, Gavriilidis, Kallinterakis and Ferreira (2013a) report that existence of increased volumes indicate that trading environment provides more liquid and rising liquidity creates a conducive environment for participation of informed traders by allowing them to see the easier execution of the trades of others. Gavriilidis *et al.*, (2013a) argue that low-abled institutional investors find high liquid environment a fertile ground for copying the trades of others, as it enables them to mimic on the highly-abled institutional investors without constraining their

herding strategy by trading frictions such as thin trading which is prevalent during lower trading activity. So, if there is herding by institutional investors, we expect to find a relationship between herding and trading volume (i.e. high volume will be associated with more herding). If the herding is not intentional, we do not expect to see herding vary with trading volume. More formally, our hypotheses are as follows:

H₁: Institutional herding depends on market volume.

H₂: Institutional herding does not depend on market volume.

To test for the effect of trading volume over herding, we use the daily market volumes i.e. observations of the Malawi Stock Exchange Index for the period January 2007 to October 2019. We aggregate the daily volume observations each quarter for the index, calculate their US dollar equivalent value. We then rank the quarterly volume observations in ascending order. We then split the dollar volume observations into two groups, lower than the median value and higher than the median value. We then split β_I and its two components according to each group.

5.4 Empirical Results and Discussion

5.4.1 Results of the full sample

We estimate for each quarter a cross-sectional (across securities) regression of the standardized fraction of institutions buying security k ($\Delta_{k,t}$) in the current quarter on the standardized fraction of institutions buying security k in the previous quarter ($\Delta_{k,t-1}$) as in equation (3) see Section 5.4.2.

We report the average coefficients from the 52 regressions and associated t -statistic (computed from the time-series standard error) in the first column of Table 5.2 (Panel A). The results are reported in Table 5.2 for stocks for which there was ≥ 1 institutional trader and ≥ 2 institutional traders. Previous studies such as Sias (2004), Gavriilidis, Kallinterakis and Ferreira (2013b) and Holmes, Kallinterakis and Ferreira (2013) report additional results for institutional traders for ≥ 3 , and ≥ 5 . However, due to the small size of the market under study, our partition is restricted.

The reported results emanate from the estimation of equation (3). They relate to the average beta coefficients over quarterly periods covered under the period 2007 to October 2019. Column 1 of Table 5.2 (Panel A) shows that the average estimates of the coefficient is positive and significant in stocks for which there was ≥ 1 institutional trader, consistent with the hypothesis that a fraction of institutional investor buying a security in the current quarter will

positively covary with the fraction of institutional investors buying a security in the previous quarter if institutional investors follow their own lag trades or if they follow each other into and out of the same securities. The coefficient associated with the lag standardized fraction of institutions buying averages 0.0876 differs significantly from zero at the 5 percent level. This means the Malawian institutional investors' demand exhibits a significant temporal dependence, as reflected through the quarterly cross-sectional correlation of institutional demand. Since the data are standardized, and there is a single dependent variable, Sias (2004) states that the coefficients in the regressions of institutional demand on lag institutional demand have a straightforward interpretation-the coefficients are the correlations. This means that the cross-sectional correlation between institutional demand this quarter and the last-quarter averages 0.0876. This beta coefficient is largely driven by the portion that represents institutional investors following their own previous trades other than the portion of correlation that represents institutions following the previous trades of other institutional investors. This finding appears to be in part consistent with previous findings in literature such as Sias (2004), Gavriilidis, Kallinterakis and Ferreira (2013b), and Holmes, Kallinterakis and Ferreira (2013).

A decomposition of the beta coefficient that represents institutions following their own trades, is positive and significant suggesting that a fraction of institutions tends to follow themselves over adjacent quarters. The portion that represents herding shows a negative sign, and is significant, suggesting that a fraction of institutional investors abandon securities that other institutional investors purchased in the previous quarter.

The second and third columns of Table 5.2, Panel A reports time series averages of each portion of equation 4 (i.e. momentum and herding) and their associated *t*-statistics (computed from time-series standard errors). Column 2 represents institutions following their own trades over adjacent quarters. The results reveal that on average the fraction of institutions buying this quarter continue to buy (sell) securities they bought (sold) in the previous quarter. This is significant at 5 percent level. Column 3 represents a proportion of institutional investors that follow other institutions over adjacent quarters. The coefficient associated with a fraction of institutions following the trades of others averages -0.229 and differs significantly from zero at the 5 percent level. This means that institutional investors buy (sell) securities that other institutions sell (buy). This finding is consistent with anti-herding literature such as Jiang and Verardo (2018) which suggest that investors act against the consensus of the market. The authors develop a dynamic measure of fund level herding. They examine USA fund stocks from 1990 to 2009 and document a negative relationship between herd behavior and skill of

managers of mutual funds. They claim that while other mutual fund managers herd for reputation reasons, others go against the trend i.e. anti-herd. They explain that difference in ability and information quality drive differences in herding by mutual fund managers.

In addition, Levy (2004) explains that professional investors are on many occasions motivated by the belief that reputation gained from outperforming competitors far outweighs the reputation gained from equal success across the board. They therefore tend to take contrary decisions to what others are doing even when they believe that the herd may be correct. This means that taking an investment decision that is against the herd signals professional investors ability. Our expectation was that the institutional investors will herd into and out of the same securities over adjacent quarters, however our findings show that they do not. The implication is that trading information of institutional investors is not readily available to the market. It is also likely the case that due to credibility issues; institutional investors prefer to trade based on their abilities. Levy (2004) state that decision makers who ignore public information and rely on their private information demonstrate confidence in their ability. Further, Chiang and Zheng (2010) explain that due to credibility issues, varying beliefs generate heterogeneous investors that impair likelihood of following each other's trades. The findings of our study are also consistent with studies such as Hung, Lu and Lee (2010) and Fang *et al.* (2017) which document that investors follow own trades than the trades of other investors due to trading costs.

When the sample is restricted to stocks traded by ≥ 2 institutional investors, the proportion of institutional investors buying a security in the current quarter positively covaries with the fraction of institutional investors buying a security in the previous quarter. The average coefficient falls from 0.0876 to 0.0675 in the restricted sample. However, it is not significant. The decomposed correlation coefficients are significant at 5 percent level. The proportion that represents institutions following themselves over adjacent quarters rises from 0.3145 to 0.4261 indicating that a larger fraction of institutional investors tends to follow their own trades when the sample is restricted. A proportion of institutional investors that follow others declines from -0.2269 to -0.3568 indicating that fewer institutional investors buy (sell) securities that other institutions sell (buy).

Table 5.2: Tests for herding-buyer if increased position.

This table reports the results from equation (3): $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$

Tests for herding- if buyer increased position			
Partitioned slope coefficient			
Average coefficient(<i>B</i>)	Institutional Investors following their own trades	Institutional investors following others' trades	Average R ²
Panel A: stocks traded by ≥ 1 institutional investors			
0.0876 (2.03)**	0.3145 (5.78)**	-0.2269 (3.52)**	0.0964
Panel B: stocks traded by ≥ 2 institutional investors			
0.0675 (1.34)	0.4261 (4.68)**	-0.3568 (-3.66)**	0.1153

For each security and quarter between January 2007 and October 2019, we calculate the fraction of institutional investors that increase their position in a security. Institutional investors are considered to have increased their position if they hold a greater fraction of the security at the end of the quarter than they held at the beginning. All data are standardized (i.e. rescaled to zero mean and unit variance) each quarter. We estimate quarterly cross-sectional regressions of institutional demand on the lag institutional demand. Because there is a single independent variable in each regression and the data are standardised, these regression coefficients are also the cross-sectional correlations between the dependent and independent variables (i.e. institutional demand and lagged institutional demand). The first column reports the time-series averages of these 52 correlation coefficients and associated *t*-statistic (in parenthesis, computed from time series-standard errors). The second column reports the portion of correlation [see Equation (2)] that results from institutional investors following their own lagged trades while the third column reports the portion of correlation that results from institutional investors following the lagged trades of other institutional investors. Panel B reports the averages when we restrict the sample to securities traded by at least two or more institutional investors. ** indicates statistical significance at the 5% level.

5.4.2 Results from market states

5.4.2.1 Results from market returns

Researchers such as Holmes, Kallinterakis and Ferreira (2013) and Gavriilidis, Kallinterakis and Ferreira (2013a,b), and using aggregate data (Lam and Qiao (2015) have examined whether institutional herding is influenced by the states of the market. These studies document relationship between institutional herding and states of market such as return, volatility and volume.

We therefore examine the influence of stock returns, volatility and trading volume over institutional herding. We begin our examination by assessing the influence of quarterly returns of the major index over institutional demand. The results are reported in Table 5.3. The average coefficients for securities that are traded by more than one institutional investor for both up-market and down- market states as well as the test of difference are not significant. However a

decomposition of the correlation coefficient shows that the coefficients are significant at 5 percent level. The portion that relates to institutional investors following their own trades has a positive sign while the portion that shows institutional investors following the trades of other investors is negative. This means that institutional investors tend to follow their own trades over adjacent quarters while the negative sign means that institutional investors tend to unwind stocks that others purchased in the previous quarter. However, the test of difference is not significant indicating that we do not find any evidence in our sample that direction of market returns influences institutional herd behavior.

When the sample is restricted to securities where at least 2 institutional investors trade, the average coefficient falls from 0.0949 to 0.036 in an upmarket while it rises from 0.07165 to 0.1361 in a down market. The decomposed coefficients are both significant at 5 percent level. The portion that relates to institutional investors following their own trades has a positive sign indicating that a fraction of investors tends to follow their own previous quarters' trades while the portion that relates to institutional investors following the trades of others has a negative sign meaning that investors unwind the positions that others purchased in the previous quarter. However, the test of difference is not significant at 5 percent level suggesting that there is no evidence of direction of market returns influencing herd behavior. Our results are inconsistent with the findings of Sias (2004) which documents that institutional investors are attracted to stocks with large lag returns. In addition, Yan and Zhang (2009) and Choi and Skiba (2015) find positive relationship between herding and returns. Mixed findings for herding effects are reported by Economou, Kostakis and Philippas (2011) for Greece during rising markets while for Portugal, Spain and Italy, they document that the effect is prevalent during days of negative market returns. Gavriilidis, Kallinterakis and Ferreira (2013a) document herding when the returns are negative.

Table 5.3: Tests for herding conditional upon market return

This table reports the results from equation (3): $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$

Partitioned slope coefficient								
Average coefficient(B)		Institutional Investors following their own trades		Institutional investors following others' trades		Average R2		
Up-market	Down-market	Up-market	Down-market	Up-market	Down-market	Up-market	Down-market	
Panel A: stocks traded by ≥ 1 institutional investors								
0.0949 (1.95)	0.07165 (0.80)	0.3071 (4.18)**	0.3307 (4.86)**	-0.2122 (-2.45)*	-0.2591 (-3.13)**		0.0858	0.1194
Test of Difference		-0.2479		0.1999		-0.3348		
Panel B: stocks traded by ≥ 2 institutional investors								
0.0362 (0.68)	0.1361 (1.22)	0.4030 (3.32)**	0.4769 (3.95)**	-0.3667 (-2.91)**	-0.3409 (-2.22)**		0.0937	0.1629
Test of Difference		0.9164		0.3743		0.1206		

For each security and quarter between January 2007 and October 2019, we calculate the fraction of institutional investors that increase their position in a security. Institutional investors are considered to have increased their position if they hold a greater fraction of the security at the end of the quarter than they held at the beginning. All data are standardized (i.e. rescaled to zero mean and unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on the lag institutional demand. Because there is a single independent variable in each regression and the data are standardised, these regression coefficients are also the cross-sectional correlations between the dependent and independent variables (i.e. institutional demand and lagged institutional demand). We then average our results across two groups, namely “high”

and “low” depending on whether the market returns during the quarter falls below the median value. The market returns are calculated every quarter as the first logarithmic difference of the quarter-end closing prices of the Malawi general market index (MASI). The first column reports the time-series averages of the correlation coefficients and associated t -statistic (in parenthesis, computed from time series-standard errors) for each of the two groups controlling for market returns. The second column reports the portion of correlation [see Equation (2)] that results from institutional investors following their own lagged trades, controlling for market returns while the third column reports the portion of correlation that results from institutional investors following the lagged trades of other institutional investors, controlling for market returns. Panel B reports the averages when we restrict the sample to securities traded by at least two or more institutional investors. ** indicates statistical significance at the 5% level.

5.4.2.2 Results from market volatility

Next, we assess the influence of market volatility over institutional herding. We examine the relative change in the quarterly volatility of the market index over institutional herding. Table 5.4 reports the results and shows in column 1 Panel A that the average coefficients for securities where more than 1 institutional investors trade are positive and significant during both periods of high and low volatility. This means that a fraction i.e. (0.0529) of institutional investors exhibit significant temporal demand during period of high volatility while a fraction (0.0813) of institutional investors exhibit significant temporal demand during period of low volatility. The decomposed coefficients show that under the proportion of institutional investors that follow their own trades over adjacent quarters, both coefficients are positive and significant under both high and low states of volatility, however the coefficient is higher during period of low volatility. For the proportion that relates to institutional investors following the trades of others, the coefficient under low volatility state is lower (i.e. more negative) than under high volatile state. The test of difference is significant indicating difference between the two states of volatile market conditions. Our empirical evidence shows that institutional demand exhibits significant temporal demand during periods of low volatility. This means that the exhibition of differences between high and low volatile market conditions are consistent with the theoretical argument of intentional herding as suggested by Sias (2004), Lobao and Serra (2007), Holmes, Kallinterakis and Ferreira (2013), Gavriilidis, Kallinterakis and Ferreira (2013a) and Lam and Qiao (2015).

When the sample is restricted to securities traded by more than 2 institutional investors (see panel B), the average coefficient under high volatile state increases from 0.0529 to 0.071 while under the low volatile state declines from 0.0813 to 0.055. However, coefficients under both states of volatility are positive and significant. The decomposed coefficients show that for the proportion that represents institutional investors following their own previous quarter trades, the coefficient marginally rises under high volatile state while under low volatile state it rises moderately. The coefficient that relates to proportion of institutions that follow the trades of other institutional investors declines under both states of volatility. The signs remain negative and significant at 5 percent level. A test of difference between the states shows significant difference indicating that there is more exhibition of temporal dependence under low volatile state of the market. The existence of herd behavior during low volatile states is consistent with the findings of Guney, Kallinterakis and Komba (2017) and Gavriilidis and Kallinterakis

(2021). These studies document presence of herding during low volatile periods for frontier markets and Russia respectively.

Table 5.4 : Tests for herding conditional upon market volatility

This table reports the results from equation (3): $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$

Average coefficient(<i>B</i>)		Partitioned slope coefficient				Average R2	
		Institutional Investors following their own trades		Institutional investors following others' trades			
High volatility	Low volatility	High volatility	Low volatility	High volatility	Low volatility	High volatility	Low volatility
Panel A: stocks traded by >=1 institutional investors							
0.0529 (7.77)**	0.0813 (9.03)**	0.2552 (33.45)**	0.3680 (29.79)**	-0.2023 (-17.08)**	-0.2867 (-22.01)**	0.0640	0.1176
Test of Difference		1.56		6.42**		-4.38**	
Panel B: stocks traded by >=2 institutional investors							
0.0710 (8.66)**	0.0550 (6.25)**	0.3016 (42.76)**	0.5628 (24.00)**	-0.2306 (-18.98)**	-0.5077 (-21.74)**	0.1030	0.0900
Test of Difference		-2.22**		9.997**		-10.37**	

For each security and quarter between January 2007 and October 2019, we calculate the fraction of institutional investors that increase their position in a security in the Malawian market. Institutional investors are considered to have increased their position if they hold a greater fraction of the security at the end of the quarter than they held at the beginning. All data are standardized (i.e. rescaled to zero mean and unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand

on the lag institutional demand. Because there is a single independent variable in each regression and the data are standardised, these regression coefficients are also the cross-sectional correlations between the dependent and independent variables (i.e. institutional demand and lagged institutional demand). We then average our results across two groups, namely “high volatility” and “low volatility” depending on whether the market volatility during the quarter falls below the median value. The market volatility is calculated every quarter using the standard deviation of daily index returns in quarterly intervals following Schwert (1989) on the basis of the Malawi All Share Index (MASI). The first column reports the time-series averages of the correlation coefficients and associated *t*-statistic (in parenthesis, computed from time series-standard errors) for each of the two groups controlling for market volatility. The second column reports the portion of correlation [see Equation (2)] that results from institutional investors following their own lagged trades, controlling for market volatility while the third column reports the portion of correlation that results from institutional investors following the lagged trades of other institutional investors, controlling for market volatility. Panel B reports the averages when we restrict the sample to securities traded by at least two or more institutional investors. ** indicates statistical significance at the 5% level.

5.4.2.3 Results from market volume

We finally examine the impact of market volume over institutional herding. Literature also suggests that stocks that register high volumes experience a high degree of return continuation. The empirical evidence is documented by studies such as Wermers (1999) and Sias (2004). We control for the influence of the relative change in the quarterly volumes of the market index over institutional herding. The results are presented in Table 5.5. In column 1 panel A, the average coefficient for securities where ≥ 1 institutional investors execute trades under both states of high and low market volumes are positive but not significant. The decomposed coefficients are both significant, however the signs are different. Under the proportion where institutional investors follow their own previous trades over adjacent quarters, the signs are positive and significant indicating that a fraction of the institutional investors follow their own previous trades during both high and low volume states. Under the proportion of the coefficient where institutional investors follow the trades of others, the sign is negative and significant indicating that institutional investors tend to unwind stocks that others purchased in the previous quarter. The test of difference is however not significant. This means that we do not find any evidence of effect of volume over institutional herding. This is however inconsistent with findings in literature where studies such as Holmes, Kallinterakis and Ferreira (2013), Gavriilidis, Kallinterakis and Ferreira (2013a) and Vo and Phan (2017) document evidence of the relationship between volume and institutional herding.

When we restrict the sample to securities traded by more than 2 institutional investors, the average coefficients under high volume state drastically reduce from 0.0746 to 0.0141 while under low volume state marginally increases from 0.0764 to 0.0783. However, the coefficients are not significant. A decomposition shows that under the proportion that relates to institutional investors following their own trades, the sign is positive and significant for both high and low volume state. Under high volume state, the coefficient marginally declines from 0.2954 to 0.286 while under the low volume state it increases from 0.3199 to 0.556. This means a fraction of institutional investors that follow their own trades largely remains the same during periods of high volume while under low volume state it increases when the sample is restricted. Under the proportion that relates to institutional investors following the trades of others, the signs are negative under both high and low volume states indicating that the investors unwind stocks that other institutional investors purchased in the previous quarter. A test of difference shows that there is no significant difference in the coefficients indicating that we do not find any evidence of the effect of volume over institutional herding. This is however inconsistent with findings

from empirical studies such as Holmes, Kallinterakis and Ferreira (2013); Gavriilidis, Kallinterakis and Ferreira (2013a) and Vo and Phan (2017) which document evidence of volume over herd behavior.

Table 5.5 : Tests for herding-controlling for market volume

This table reports the results from equation (3): $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$

Partitioned slope coefficient								
Average coefficient(B)		Institutional Investors following their own trades		Institutional investors following others' trades		Average R2		
Panel A: stocks traded by ≥ 1 institutional investors								
High volume		Low volume	High volume	Low volume	High volume	Low volume	High volume	Low volume
0.0746 (1.61)		0.0764 (1.07)	0.2954 (5.29)**	0.3199 (3.32)**	-0.2208 (-3.26)**	-0.2436 (-2.14)**	0.0598	0.1167
Test of Difference		0.02		0.22		-0.17		
Panel B: stocks traded by ≥ 2 institutional investors								
0.0141 (0.24)		0.0783 (1.07)	0.2860 (5.84)**	0.5556 (3.14)**	-0.2719 (-4.39)**	-0.4773 (-2.55)**	0.0849	0.1197
Test of Difference		0.69		1.47		-1.04		

For each security and quarter between January 2007 and October 2019, we calculate the fraction of institutional investors that increase their position in a security. Institutional investors are considered to have increased their position if they hold a greater fraction of the security at the end of the quarter than they held at the beginning. All data are standardized (i.e. rescaled to zero mean and unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on the lag institutional demand. Because there is a single independent variable in each regression and the data are standardised, these regression coefficients are also the cross-sectional correlations between the dependent and independent variables (i.e. institutional demand and lagged institutional demand). We then average our results across two groups, namely “high volume” and “low volume” depending on whether the market volume during the quarter falls below the median value. The Malawi All Share Index (MASI) is used to calculate market volume. Market volume is calculated every quarter by aggregating the daily volumes observations on the Malawi All Share Index every quarter. The first column reports

the time-series averages of these correlation coefficients and associated t -statistic (in parenthesis, computed from time series-standard errors) for each of the two groups controlling for market volume. The second column reports the portion of correlation [see Equation (2)] that results from institutional investors following their own lagged trades, controlling for market volume while the third column reports the portion of correlation that results from institutional investors following the lagged trades of other institutional investors, controlling for market volume. Panel B reports the averages when we restrict the sample to securities traded by at least two or more institutional investors. ** indicates statistical significance at the 5% level.

5.4.3 Test for momentum trading

The empirical studies of Grinblatt, Titman and Wermers (1995); Nofsinger and Sias (1999), Wermers (1999) and Sias (2004) suggests that institutional investors as a group engage in momentum trading. Sias (2004) suggests that momentum trading by institutional investors is a form of characteristic herding i.e. institutional investors herd to (herd away from) stocks with high (low) past returns. The study explains that institutional investors herd into and out of the same stocks because institutional investors are momentum traders and the lag fraction of institutions buying proxies for lag return.

To evaluate momentum trading and its effect in explaining the relation between the fraction of institutions buying and the lag fraction of institutions buying, we follow the methodology of Sias (2004) by adding a lag return as a standardized independent variable to Equation (3). For each quarter, we cross-sectionally regress (across K securities) the quarterly standardized fraction of institutions buying on the lag quarterly standardized fraction of institutions buying and lag quarterly standardized return²⁸ :

$$\Delta_{k,t} = \beta_{1,t} \Delta_{k,t-1} + \beta_{2,t} R_{k,t-1} + \varepsilon_{k,t} \quad \dots\dots\dots(5)$$

We report the average coefficients from the 52 regressions and associated t -statistics (computed from the time-series standard errors) in Table 5.6. The results for the sample that includes all securities with at least 1 and 2 institutional trader(s) are reported in panels A and B, respectively.

²⁸ Standardized return is computed by replacing the fraction of institutions buying with the return in Equation (2)

Table 5.6: Standardized regression of institutional demand on lag institutional demand and lag return

$$\Delta_{k,t} = \beta_{1,t} \Delta_{k,t-1} + \beta_{2,t} R_{k,t-1} + \varepsilon_{k,t}$$

Average coefficient associated with lag institutional demand	Average coefficient associated with lag return	Average R ²
Panel A: stocks traded by >=1 institutional investor		
Regression 1-Buyer increased position		
0.0876 (2.03)**	0.0472 (3.28)**	0.0964
Panel B: stocks traded by >=2 institutional investors		
0.0675 (1.34)	0.0472 (3.28)**	0.1153

For each security and quarter between January 2007 and October 2019, we calculate the fraction of institutional investors that increase their position in a security. Institutional investors are considered to have increased their position if they hold a greater fraction of the security at the end of the quarter than they held at the beginning. All data are standardized (i.e. rescaled to zero mean and unit variance) each quarter to allow direct comparison between the coefficients associated with independent variable. We estimate quarterly cross-sectional regressions of institutional demand on the lag institutional demand and lag quarterly return. The first column reports the time series average (standardized) coefficients from the 52 cross-sectional regressions and associated *t*-statistic (in parenthesis, computed from time series-standard errors). The second column reports the average coefficient associated with lag return. Panel B reports the averages when we restrict the sample to securities traded by at least two or more institutional investors. ** indicates statistical significance at the 5% level.

Our results in Table 5.6 show that, for all securities with at least one institutional trader, the coefficient associated with lag standardized returns averages 0.0472 (statistically significant at 5 percent level). Since the data are standardized, as interpreted by Sias (2004) this suggests that a one standard deviation increase in last quarter return is associated with a 4.72 percent standard deviation greater fraction of institutions buying this quarter. We find that adding a standardized lag return to the regression has no effect at all on the average coefficients. It implies that since investors are following the wrong trades, the past returns coefficient does not affect the coefficient of institutional demand.

5.4.4 Summary of overall result

The overall result of our investigation means that institutional investors in Malawian do not follow other institutional investors in contrast with the findings by such studies as Sias (2004), Gavriilidis, Kallinterakis and Ferreira (2013b), and Holmes, Kallinterakis and Ferreira (2013) which document herd behavior among institutional investors. One of the reasons could be that institutional investors do not easily monitor the action of others. The other reason could be the disclosure policy which does not require institutional investors to disclose their trades. Contrasting with developed economies such as the US, where the reporting requirements require that all investment managers with at least \$100 million in assets under management disclose their equity holdings by filling in 13F reports, which are comprehensive, this is not the case with Malawi. Filing in 13F allows the US public to get a view of the holdings of the institutional investors in the country. In the case of Malawi, institutional investors are required to report but only global figures such that an institutional investor would not see which securities others are invested in. The reporting template is far less detailed, and the reports are not made public. The regulator publishes an annual report that summarises holdings of all institutional investors in the market. The empirical finding implies that trading information of institutional investors is not conveyed to the market. In the case of no information, institutional managers tend to follow a momentum strategy.

5.5 Conclusion

The paper examines herding as a determinant of the temporal dependence of institutional investors demand in Malawi market and investigates whether specific market conditions provide an enabling environment for this trading behavior. We examine this trading behavior by analysing institutional portfolio holdings of institutional investors for the period January 2007 to October 2019. We ascertain the motivation of institutional herding by analysing the interaction of the behavior with market factors such as returns, volatility and trading volume. We find that institutional investors do not engage in herd behavior because the trading information of other institutional investors is not easily available. Bikhchandani and Sharma (2000) state that herding occurs if there is sufficient homogeneity i.e. investors face a similar decision problem and so trade actively and take similar action. They state that the homogenous group need not be too large. In this study, Malawian institutional investors do not exhibit homogeneous investment decisions. The finding means that Malawian institutional investors do not follow the trades of others. The finding implies that institutional investors trading information is not filtered to the market suggesting an informationally inefficient market.

6.0 Conclusion

6.1 Conclusion & Implications

In conclusion, the aim of the thesis is to contribute to existing literature on investor behavior by examining concepts in behavioral Finance, particularly sources of feedback trading and one of the forms of collective behavior namely institutional herd behavior. These concepts are important because they have potential to harm price efficiency and economic growth.

We first examined whether the misconduct of market intermediaries i.e brokers enables them earn higher returns than outside investors. It is suggested in literature that market intermediaries abdicate their role in ensuring price efficiency, speculate by creating feedback trading and eventually distort prices. We then investigate whether investors have the tendency to sell winners too early and hold onto losers for too long. We also examine whether their behavior is influenced during the period when taxes are due. Finally, we examine whether institutional investors mimic the trades of other institutional investors, and whether market conditions influence their herd behavior.

We review literature relating to the matters under study and provide empirical evidence in Chapter 2. In Chapter 3 we examine the first research question regarding the relationship between level of principalness by brokers and their trading profits. Specifically, we analyze trading patterns to compare trading profits between market intermediaries and outside investors. With the hypothesis that the brokers profitability is related to the degree of their principalness, we test the profitability differentials between principal brokers and outside investors using the methodology of Khwaja and Mian (2005). By testing our hypothesis using Malawi data, we find that there is no evidence that brokers manipulate the stock prices in the market. Given that theory informs us that brokers use information asymmetry and their position to manipulate stock markets, our empirical results are in contrast with the theory. An explanation of this finding is that the limited numbers of brokers and thin trading in the market, would probably make price manipulation noticeable and so brokers find it difficult to engage in it. It is also probable that since brokers are allowed by regulation to engage in limited fund management where they generate supplementary income, they probably live on it sufficiently to discourage them from manipulative action. An implication of the finding is that LDC's probably have efficiency enabled by the integrity of the brokers and motivating legislation. The study documents empirical evidence to the body of literature on price destabilization.

In Chapter 4 we investigate the extent of the prevalence of disposition effect among investors and explain potential causes in Malawi. The model of disposition effect predicts that investors realize more gains relative to the number of gains available for realization and realize fewer of the losses relative to number of losses available. Specifically, we utilize the Odean (1998) measure to calculate realized gains and realized losses for each investor and then aggregate over all investors and trading days for the entire sample period from 2013 to 2019. We then set up proportions namely Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR) and compare the differences between PGR and PLR. The difference between the average PGR and PLR for each category is tested for statistical significance using a one tailed test. A significant difference suggests that on average investors are willing to realise one element over another.

Our primary finding show that investors sell winning stocks more readily than losing stocks. The disposition effect appears to decline over time. We also find that the disposition effect does not translate into momentum trading. This finding is consistent with the study of Barber *et al.*, (2007). Our findings show that individual investors are more prone to disposition bias than institutional investors. Our findings shows that a test of rebalancing indicates that there is evidence of disposition effect. However, when the test controls partial sales for rebalancing, the study does not find significant results. The study does not find any evidence that selling decisions are influenced by transaction costs. Some evidence of presence of disposition effect implies that transmissiion of price information in the Malawi market may be hampered and regulators need to be vigilant with action of experienced investors who have potential to make money off irrational investment decisions of the less sophisticated investors. This means that there is irrational pattern in investment decision making by some investors. At an aggregate level, Plebner (2017) suggests that this may impair market efficiency and in extreme case cause total market failure and welfare losses.

In Chapter 5 we investigate herding as a determinant of the temporal dependence of institutional investors demand in the Malawi market and examine whether specific market conditions provide an enabling environment for this trading behavior. We analyze institutional portfolio holdings of institutional investors and ascertain the motivation of institutional herding by analysing the interaction of the behavior with market factors such as returns, volatility and trading volume. We deploy the methodology of Sias (2004) and find that Malawian institutional investors do not engage in herd behavior because the trading information of other institutional investors is not easily available. This means that Malawian institutional investors

do not follow the trades of others consistent with the findings of Hung *et al.*, (2010) and Fang *et al.*, 2017. The finding implies that institutional investors trading information is not filtered to the market suggesting an informationally inefficient market. The finding of anti-herding may indicate some that institutional investors ignore riding a trend and so utilise their own information and take decisions that are against the consensus.

We expected to find evidence of price manipulation and institutional herding in our study, however our results are not what we expected. The lack of evidence of price manipulation implies that existence of the regulation may have an impact on the integrity of the brokers which potentially affects their trading conduct in the Malawi market. However, the lack of evidence for institutional herd behavior implies that institutional investors trading information is not filtered to the market suggesting an informationally inefficient market.

Appendix 1

Profitability Calculation Example: ARR= the annualized nominal rate of return based on the brokers total net profit (1675615.2) for a given average capital investment (18192324). i.e. sum column 10//# of days

Average running profit divided by average net capital using this example gives us 0.921 %. ARR would then be the annualized equivalent of this rate of return using 1239 days(from 28 Oct 2011 to 20 March 2015) in this example which is 0.21

Date	Shares sold (1)	shares bought (2) Raw data	Stock price (3)	Net shares bought (4) =(2)-(1)	Share inventory (5) Running sum of (4)	Revenue (6) (3)*- (4): if (4)<0	Investment (7) (3)*(4): if (4)>0	Gross Capital required (8) (5) *(3)	Net running profit (9)	Net capital required (10)
1	0	5000	110	5000	5000	0	550000	550000	-550000	1100000
2	3000	0	130	-3000	2000	390000	0	260000	-160000	420000
3	2000	0	130	-2000	0	260000	0	0	100000	0
4	0	4794	135	4794	4794	0	647190	647190	-547190	1194380
5	0	206	135	206	5000	0	27810	675000	-575000	1250000
6	0	5000	140	5000	10000	0	700000	1400000	-1275000	2675000
7	0	1500	292	1500	11500	0	438000	3358000	-1713000	5071000
8	0	2416	292	2416	13916	0	705472	4063472	-2418472	6481944
9	13911	0	294.2	-13911	5	4092616.2	0	1471	1674144.2	0
10	5	0	294.2	-5	0	1471	0	0	1675615.2	0
EoPL			294.2	0	0	0	0	0	1675615.2	18192324

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