

UNIVERSITY OF CAPE TOWN



**Herding by South African Equity Unit Trusts:  
An analysis of the causes and extent of herding behaviour on the  
JSE Limited**

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## **Abstract**

This dissertation examines whether South African equity unit trusts follow each other into and out of the same shares (i.e., herd), and specifically whether such herding is motivated by intent. This dissertation ascertained intent by observing the interaction of correlated trading behaviour and states of the general equity market, controlled for conditions that drive spurious correlation; namely, net fund flows and momentum/ share size trading strategies. Employing the Sias measure, the empirical results reveal strong evidence of equity unit trust herding at the individual share-level for the period December 2012 – March 2020. This dissertation further examined the reputational and informational herding hypotheses and provided evidence that unit trust managers’ reputational/career concerns, as well as informational incentives contributes to unit trust herding in shares, with aggregate herding 19% more prevalent in down markets than in up markets, 36% more in low relative to high market return states, 12% more prevalent in volatile markets than in tranquil markets, and 30% more in increasing relative to decreasing market volatility states. However, this dissertation found only statistically weak evidence of herding motivated by intent under varying market states. Furthermore, there is evidence that South African equity unit trusts follow other unit trusts in large capitalisation shares (after controlling for “blue-chip” benchmark herding) and unit trusts tend to follow their own trades in small cap shares. In sum, the results provide strong evidence of herding across the unit trust industry, but this is not conclusively predicated by intent.

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## Chapter 1: Introduction

Previous research has provided a theoretical foundation and empirical evidence of herding behaviour to varying degrees at the individual share, industry and market level across emerging and developed markets. At least five main motivations for herding behaviour have been identified: due to reputational/career concerns (reputational herding), informational herding (informational cascades), correlated signals (investigative herding), relative homogeneity of investors (common investor styles or characteristic herding), and underlying investors' flows. The first two theories (reputational and informational herding) are consistent with herding hypotheses motivated by intent, while the latter theories are consistent with herding due to spurious (i.e., unintentional) motives.

— *Herding motivated by intent:*

Reputational herding occurs when investors imitate the trading actions of their peers to preserve their reputation or career – a phenomenon more pronounced in the case of professional unit trust managers whose relative performance assessment and related compensation arrangements motivate herding behaviour (Bikhchandani & Sharma, 2000; Clement and Tse, 2005; Holmes et al., 2013). Informational herding occurs when investors disregard their own private information/signals in favour of imitating their peers when they perceive other investors to have superior information(-processing) skills – which, in the extreme case, may lead to informational cascades (Bikhchandani et al., 1992; Welch, 1992; Devenow & Welch, 1996; and Bikhchandani & Sharma, 2000).

— *Unintentional herding:*

On the other hand, investors may correlate their trading actions unintentionally and merely present the impression of herding while acting on the same information signals (correlated signals), as a result of relative homogeneity in make-up of the investor base (for example, due to similarities in their educational background, investment experience, or common regulatory framework), or due to similar investor styles which shapes investors' preferences for shares with similar characteristics (De Bondt & Teh, 1997; Wermers, 1999; Barberis and Shleifer, 2003; Voronkova and Bohl, 2005; Gavriilidis et al., 2013). Finally, investors may present the impression of herding simply due to the time-series cross-correlation in their underlying fund flows (Sias, 2004).

The results of previous empirical work (e.g., Wermers 1999; Sias 2004; Choi and Sias 2009; and Brown et al., 2014) largely supports the investigative herding, style investing, and informational cascades explanations of herding behaviour, while more recent work (e.g., Holmes et al., 2013; Gavriilidis et al., 2013; Popescu & Xu, 2014; and Popescu & Xu, 2018) has contributed to the reputational herding hypothesis. Yet, given the mixed empirical results across the literature, previous studies also suggest that these explanations are not mutually exclusive.

In this dissertation – consistent with recent empirical work – presents evidence that reputational herding may also contribute to herding within South African equity unit trusts. Previous formative studies have demonstrated the link between the behaviour of unit trust managers (particularly their tendency to herd in shares and industries) and their reputational concerns. The rationale for this hypothesis resides on the notion that acting alone is costlier than acting with the group – specifically, contrarian behaviour is only mildly rewarded in event of success yet is harshly criticised in event of failure (Scharfstein and Stein, 1990; Dasgupta et al, 2011b; Popescu & Xu, 2014; and Popescu & Xu, 2018).

Following the approach of previous studies (Holmes et al., 2013; Gavriilidis et al., 2013; Popescu & Xu, 2014; and Popescu & Xu, 2018), this dissertation tests the reputational herding hypothesis by examining the interaction between unit trust herding and states of the market – specifically, it is hypothesized that the extent of herding (correlated trading behaviour) arising from equity unit trusts following their peers increases in down and up markets relative to middle market returns performance, and is more pronounced in down markets owing to asymmetric reputational and/or career concerns (i.e. the incentives to herd arising from reputational and/or career costs is greater in bear than in bull markets).

This dissertation further tests the informational payoffs hypothesis (exhibited in Holmes et al. (2013) and Gavriilidis et al. (2013)) by examining the interaction between unit trust herding and market volatility as well as share size. The premise of these arguments is that information uncertainty (or ambiguity) – prevalent in more volatile markets and in small shares with less information transparency – may drive herding behaviour when funds attempt to resolve their uncertainty by following the trades of their peers.

In this dissertation, robustness tests are also performed to control for other potential explanations for the difference in herding behaviour across market states (returns and

volatility). Specifically, the method controls for the impact of net fund flows, momentum, and share size trading strategies. The results of this dissertation suggest that equity unit trusts intentionally herd in shares, which is, at least in part, motivated by reputational and/or informational payoffs.

The remainder of this paper is organised as follows: chapter 2 presents the theoretical motivations and empirical results of previous international herding studies, including potential motivations for herding behaviour; chapter 3 discusses the methodology and data used for the analysis in the South African equity unit trust market; chapter 4 presents and discusses the empirical results; chapter 5 provides concluding remarks; and finally, chapter 6 proposes areas for further research.

## Chapter 2: Literature review

This section provides an overview of the existing herding literature, including theoretical motivations and empirical results of previous international herding studies. First, herding is defined in the context of this dissertation, followed by the implications of examining herding behaviour within the South African equity market. Finally, the main theories underlying herding behaviour are summarized with specific focus on the causes of herding identified in previous work.

### *2.1 Institutional herding: setting the context*

Herding behaviour is broadly defined as the tendency for a group of investors<sup>1</sup> to imitate the trading actions of others. Investors herd when they accumulate on the same side of the market or follow the lead of others when they trade (Hsieh, 2013). Herding behaviour can be motivated by intent (*intentional herding*) or merely by the result of investors' correlated signals (*spurious herding*). The concept of herding has been explored in various international studies, with evidence from the existing literature confirming the presence of herding at varying degrees within the individual share, industry and market level<sup>2</sup>.

While the methodology and results of these studies are not entirely consistent, it is clear that herding is found to be stronger in emerging markets compared to developed ones which could be attributed to relatively less information transparency (higher informational ambiguity) in emerging markets, “prompting investors to resort to herding as a means of resolving this ambiguity” (Gelos & Wei, 2005; and Guney et al., 2017). For example, fund managers tend to exhibit higher levels of herding in South Korea (Choe et al., 1999), Taiwan (Chang, 2010; Lu et al., 2012), Portugal (Holmes et al., 2013), and South Africa (Abrahamson, 2017) compared to Spain (Gavriilidis et al., 2013), the UK (Wylie, 2005), Germany (Walter and Weber, 2006; Kremer and Nautz, 2013) and the US (Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999; Sias, 2004; and Choi & Sias, 2009).

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<sup>1</sup> This dissertation examines herding at the share level with the focus institution group being equity unit trusts – throughout, this paper has used the terms investors, funds, fund managers, and institutions interchangeably.

<sup>2</sup> Refer to Table 2 for the results of comparable international herding studies which is discussed further in chapter 2.1 of this paper. For comparability, this paper only included the results of studies with similar herding methodology (i.e., those that adopted the measure first proposed by Sias (2004), which was used within this dissertation).

The question of herding with intent has received relatively little focus outside of theoretical proposition. This could be on account of inhibiting practical factors such as data constraints and methodological challenges in distinguishing intentional from spurious herding results. The focus of this paper is on intentional herding and attempts to employ methodologies used in two such herding studies first undertaken within the Portuguese unit trust share level (Holmes et al., 2013) and the Spanish unit trust industry level (Gavriilidis et al., 2013).

Holmes et al. (2013) first proposed that intent could be exhibited when the extent (significance) of institutional herding varied between different states of the market (considering market returns, volatility and regulatory changes); conversely, if fund managers herded spuriously, the significance of such behaviour should be unaffected by the market's state. Holmes et al. (2013) presented various hypotheses to gauge herding in Portuguese unit trusts under these specific market states. Holmes et al. (2013) found strong evidence of herding interaction under all aggregate market conditions by univariate analysis. In addition, by multivariate analysis, Holmes et al. (2013) found strong evidence of herding motivated by intent notably in periods of declining/low market-wide returns and changing regulatory conditions that was introduced to promote information transparency; yet there was no significant herding interaction under conditions of varying market volatility. The findings in Holmes et al. (2013) suggested that Portuguese fund managers herd intentionally, consistent with poor-quality fund managers following the actions of good quality fund managers.

Gavriilidis et al. (2013) performed a similar study with Spanish unit trusts at the industry level by controlling for market as well as individual sector conditions – conditioned on returns, volatility, and trade volume for the sector and market as a whole. Gavriilidis et al. (2013) found strong evidence of intentional herding at the overall market level as well as specific sector level under conditions of declining/low returns, rising/high volatility and rising/high trading volume. The first condition (declining/low returns) is consistent while the second condition (rising/high volatility) is inconsistent with the results of Holmes et al. (2013). Gavriilidis et al. (2013) attributed this behaviour due to intent under informational and reputational herding motives<sup>3</sup>.

The studies performed by Holmes et al. (2013) and Gavriilidis et al. (2013) were conducted within emerging markets characterised by lower information transparency (Gelos & Wei, 2005;

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<sup>3</sup> Refer to chapter 2.3 for analysis of suggested motives for herding behaviour.

and Guney et al., 2017), and was thus comparable with the South African equity market forming the context of this dissertation.

## ***2.2 Implications of herding behaviour***

It is commonly assumed in economic practice that humans are motivated by the prospect of maximising their wealth (Scott, 2000). This so-called “rational choice theory” allows us to “construct formal – and often predictive – models of human behaviour” (Scott, 2000). In the context of this dissertation, the “rational choice theory” was translated to mean that investors will seek to maximise the profit on their overall portfolio holdings. This implies that investors will herd intentionally when they expect a positive payoff from discarding their own private signals in favour of imitating other investors, particularly in the case of investment professionals (fund managers) whose performance is assessed on a regular and relative basis to their peers (Gavriilidis et al., 2013; and Guney et al., 2017).

Moreover, classical economic theory is built on the basis that free agents make economic decisions using all available information in an efficient manner (Scharfstein & Stein, 1990). This means that professional investment managers will make well-informed investment decisions to maximise their wealth, as premised in rational choice theory. On the other hand, investment decisions are also partly driven by group psychology which weakens the link between information and market outcomes (Scharfstein & Stein, 1990). Hence, to the extent that investment decisions diverge from the classical economic and rational choice theories, group psychology may play a role in driving sub-optimal market outcomes. One such group psychology is manifested in the herding effect. It is therefore important to understand the reasons that unit trust investors diverge from these economic theories in favour of supposedly irrational herd-like behaviour.

Existing literature reveal an interaction between herding behaviour and share prices leading to the prognosis that institutional investors, in particular, may herd into and out of shares without fundamental justification (Scharfstein & Stein, 1990; Wermers, 1999; and Bikhchandani & Sharma, 2000). Because of the dominance of institutional investors in stock markets that drive high trading volumes, this kind of institutional herding is suspected to dilute the information quality of share prices, exacerbate share price volatility, increase the fragility of the financial

system, and destabilise capital markets by driving prices away from fundamentals<sup>4</sup> (Scharfstein & Stein, 1990; Wermers, 1999; Bikhchandani & Sharma, 2000; and Walter & Weber, 2006).

Moreover, intentional herding as a behavioural phenomenon only exists where investors disregard their own information in favour of following the trades of others. As such, this phenomenon distorts the theories of market efficiency whereby asset prices reflect only available and fundamental market information. This then has further implications for how underlying asset prices are determined.

As previously mentioned, investors may diverge from their planned decisions in favour of imitating others due to intentional or spurious motives (Bikhchandani & Sharma, 2000). Existing literature suggest several reasons for the profit-maximising investor to be influenced into diverging from their planned decisions in favour of imitating others<sup>5</sup>.

Professional fund managers are often rewarded for superior returns performance. The link between the professional payoffs and asset allocation decisions – or more directly, fund holdings decisions – suggests that such herding behaviour could be rewarded. Therefore, the findings of this dissertation have important implications for the way investors (principals) monitor and reward professional fund managers. Moreover, herding as a result of the reputational and/or information payoffs may create an incentive for poor-quality fund managers to follow others perceived to possess superior information (-processing) skills, which creates ambiguity in the performance assessment process (Gavriilidis et al., 2013). Put simply, herding behaviour may give poor-quality managers the opportunity to conceal their poor trade decisions, while at the same time making it difficult for principals to distinguish high- and poor-quality managers from one another.

While the phenomenon of herding has been studied extensively, very few studies have given attention to drivers of such behaviour within the South African market, particularly when

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<sup>4</sup> Herd trading and momentum investing strategies have a destabilizing effect on capital markets when institutions purchase overpriced and sell underpriced shares, resulting in asset prices being driven further away from their fundamental values. However, Wermers (1999) and Lakonishok et al. (1992) argue that herding and momentum investment strategies need not always have a destabilizing effect on capital markets, yet may, in fact, speed up the price-adjustment process by which assets reflect their fundamental values, thereby actually improving capital market efficiency.

<sup>5</sup> Refer to chapter 2.3 for analysis of suggested motives for herding behaviour.

motivated by intent. There has also been relatively little focus of herding studies in the South African unit trust industry (other than one study performed by Abrahamson, (2017)). This paper attempts to fill the gap in this literature. Specifically, it contributes to the existing literature on herding behaviour in unit trusts by examining herding at the share level within South African equity unit trusts.

### ***2.3 Proposed motivations for herding behaviour***

At least five main motivations have been provided for professional fund managers to herd in securities, due to intent and spurious factors.

— *Herding motivated by intent:*

In the case of intent, fund managers may herd due to reputational concerns (*reputational herding*) (Scharfstein & Stein, 1990; Zwiebel, 1995; Sias, 2004; Dasgupta et al., 2011a,b; Popescu & Xu, 2014; and Popescu & Xu, 2018) and inferring information from each other's trades when they perceive other investors to have superior information(-processing) skills (Bikhchandani et al., 1992; Welch, 1992; Devenow & Welch, 1996; and Bikhchandani & Sharma, 2000).

In the case of *reputational herding*, the anticipation of professional payoffs for a fund manager – linked to the compensation incentives and terms of employment – may be such that imitation is rewarded (Bikhchandani & Sharma, 2000; Clement and Tse, 2005; Holmes et al., 2013). The reason for this is that contrarian behaviour is only mildly rewarded if it results in a successful decision outcome, yet is harshly criticised if it results in an unsuccessful decision outcome (Scharfstein & Stein, 1990). Keynes (1936) similarly expressed that “it is better for reputation to fail conventionally than to succeed unconventionally”.

Moreover, investors may disregard their private signals in favour of imitating others due to *informational payoffs* (Devenow & Welch, 1996), which may, in the extreme case, drive informational cascades when trades converge on the same limited information set (Banerjee, 1992; Bikhchandani et al., 1992).

— *Unintentional herding:*

Herding may also be driven by spurious factors owing to investors following correlated signals (*investigative herding*) (Froot et al., 1992; Hirshleifer et al., 1994; and Choi & Sias, 2009), following fads (Friedman, 1984), or chasing certain characteristics (*characteristic trading*) (Falkenstein, 1996; Bennett et al., 2003; and Sias, 2004). There may be relative homogeneity amongst investment professionals – due to similarities in their educational background, investment experience, common regulatory framework, and how similar informational signals are received and processed – which may lead to unintended correlated trading activity (De Bondt & Teh, 1997; Wermers, 1999; Voronkova & Bohl, 2005; and Gavriilidis et al., 2013). Common investing styles may generate the impression of herding; for example, positive-feedback or momentum trading investors may cumulatively herd into recent winners and out of recent losers and are thus merely responding simultaneously and identically on the same information-set in response to similar decision problems (Walter & Weber, 2006)<sup>6</sup>. Spurious herding may also arise due to capital or fund mandate constraints such that the opportunity sets of different investors may differ (Bikhchandani & Sharma, 2000).

Other studies have theorized that retail fund flows can also contribute to herding behaviour. This was disputed by Choi & Sias (2009) where they found no evidence that institutional industry herding in the US market is driven by retail investors' flows, after controlling their sample of institutions for retail investment entities such as unit trusts and independent investment advisors.

The timing of quarterly reported earnings results in the South African unit trust industry may explain intentional herding (akin to the 'window dressing' explanation provided by Lakonishok et al. (1991)). According to this approach, fund managers may sell past losers and "dress up" their portfolio with past winners due to reputational concerns, especially at the end of a fiscal

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<sup>6</sup> Sias (2004) argued that investors as a group may herd spuriously as a result of being attracted to securities with similar characteristics (deemed "habit investing") and, with changing net fund flows, will simply adjust their portfolios simultaneously over adjacent periods which may, in turn, generate the impression of herding. This dissertation controlled for such spurious trading due to net fund flows by analysing changes in fractional share ownership across quarters rather than absolute holdings. This method of analysing changes in portfolio weights also inherently controls for changes in shareholdings that may arise without associated trading activity (e.g., share-splits, share dividends, capitalisation and bonus issues) that would otherwise generate the impression of herding.

reporting period (Walter & Weber, 2006; and Holmes et al., 2013)<sup>7</sup>. Walter & Weber (2006) further noted that the consequences of making bad investment decisions are not as severe when the manager's peers made the same mistakes, which further reinforces the motive for professional fund managers to herd intentionally (akin to the reputational herding hypothesis referred to earlier).

Various studies have captured intentional herding through examination of the interaction of herding behaviour under different market states, including returns performance (Chang et al., 2000; Cooper et al., 2004; Rosen, 2006; Holmes et al., 2013; Gavriilidis et al., 2013; Popescu & Xu, 2014; and Popescu & Xu, 2018), level of market volatility (Zhang, 2006; Kearney & Poti, 2008; Holmes et al., 2013; and Gavriilidis et al., 2013) and the regulatory environment (Chung et al., 2004; Antoniou et al., 2005; Chau et al., 2008; Holmes et al., 2013). As hypothesised in Holmes et al. (2013) and Gavriilidis et al. (2013), intentional herding can be captured if any of these market or sector factors impact the extent (or level) of the herding measure. The market returns and market volatility arguments are considered in turn.

### *2.3.1 Market returns*

Market returns may be expected to impact herding due to reputational and/or information payoffs. As previously mentioned, contrarian behaviour is only mildly rewarded in times of success, yet is harshly criticised in times of failure. As such, when the market is performing poorly – creating conditions where it is more likely for equity funds to generate losses – investor returns (i.e., fund performance) suffer greater scrutiny from principal stakeholders which incentivises fund managers to follow their peers to claim that they performed (at least) no worse than their fellow traders. This pressure to perform is even more pronounced in the case of unit trust managers as a set of broader institutional investors given that fund performance is typically assessed on a regular and relative basis to peers, highlighting the propensity to herd due to reputational and/or career concerns<sup>8</sup> (Gavriilidis et al., 2013; Popescu

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<sup>7</sup> The 'window dressing' explanation has not been examined in this paper due to data constraints (refer to chapter 3.2 for further detail), while this topic has been included as an area for further research within chapter 6.

<sup>8</sup> Sias (2004) also argued that, if reputational or career concerns contribute to herding behaviour, institutional investors are more likely to follow similarly classified institutions than differently classified institutions. This is consistent with empirical results presented by Popescu & Xu (2014) who demonstrated that institutional investors with higher reputational concerns (e.g. unit trusts) tend to follow their peer investors with similar reputational

& Xu, 2014; and Guney et al., 2017). Moreover, one would expect that poorer quality fund managers exhibit more pronounced herding behaviour during down markets when they perceive other fund managers to hold superior information (-processing) skills (*informational payoffs*) (Bikhchandani et al., 1992; Welch, 1992; Devenow & Welch, 1996; and Bikhchandani & Sharma, 2000). In an upturn, one would expect similar intentional herding behaviour owing to scrutiny of relative fund performance – since “underperforming during periods of rising prices is more easily associated to low ability” (Gavriilidis et al. (2013)). Consistent with these insights, through examination of risk-taking behaviour of US equity fund managers across different market states, Kempf et al. (2009) demonstrated that fund managers’ decisions are influenced, at least in part, by their desire to keep their jobs (employment incentives) during down (or bear) markets and to earn higher compensation (compensation incentives) during up (or bull) markets.

Popescu & Xu (2014, 2018) found evidence of reputational herding through investigation of market returns performance, noting that herding was more pronounced (i.e., up to 71% more likely to occur) in a bear market than in a bull market. This is consistent with the results of studies performed by others (e.g., Kempf et al., 2009; Holmes et al., 2013; and Gavriilidis et al., 2013) but is inconsistent with the results of Walter & Weber (2006) who presented evidence of significantly stronger herding tendencies in bull over bear markets<sup>9</sup>.

The impact of market returns and spurious herding motives are considered next. Herding as a result of relative homogeneity in fund managers (for example, due to similar educational backgrounds or experience) would not itself be expected to interact with the level of market returns given that the quality and composition of fund managers as a group is not expected to change significantly from quarter-to-quarter or under different market states (Holmes et al., 2013; and Gavriilidis et al., 2013). Further, while it is possible that fund managers trade together as a result of correlated signals during periods of poor market performance, one could expect that such correlated trading is not directly related to the performance of the market as a

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concerns. As such, one would expect that equity unit trusts would more likely follow other equity unit trusts. This logic is also in line with the arguments regarding relative peer assessment and “benchmark herding” presented later.

<sup>9</sup> The difference in outcome of these studies could be explained by market or time-period differences, as well as methodological differences; Popescu & Xu (2014, 2018) employed the Sias measure in the US market, while Walter & Weber (2006) employed the LSV measure to gauge industry herding in German mutual funds. We analysed the methodological differences between the Sias and LSV measures later in chapter 3.

whole but is more-so with individual share returns and fundamentals. Holmes et al. (2013) contend that characteristic trading strategies (e.g., momentum trading, contrarian, and value-vs-growth investing) are, in practice, based on relative measures (e.g., P/E ratios, and dividend yields) rather than absolute values of returns. Hence, one would not expect the extent of characteristic trading (or tendency of investors to style-invest) to be directly and systematically affected by market-wide returns, *ceteris paribus*.

### *2.3.2 Market volatility*

In traditional finance theory, market volatility is seen as a proxy for risk and uncertainty. During periods of higher market volatility, fund managers (especially poor-quality managers) may seek to resolve their uncertainty by following the trades of their peers due to their perceived superior information (-processing) skills. This may arise from the (lack of) skills required to decipher content arising from increased information flows during volatile environments (Gavriilidis et al., 2013). In contrast, during periods of lower market volatility, it is easier to distinguish poor from superior quality fund managers in the assessment of relative fund performance which may result in herding due to reputational concerns (Holmes et al., 2013). One can therefore expect the level of volatility to impact the extent of intentional herding, albeit the nature of association is ambiguous (Holmes et al., 2013). Put simply, if fund managers herd intentionally, one would expect to exhibit differences in the herding measure when controlling for market volatility; conversely, if herding is spurious, one would expect to observe no significant differences in the aggregate herding measure across states of market volatility.

While it is possible that spurious correlated trading occurs around periods of extreme market volatility, for similar reasons expressed in chapter 2.3.2 above, it is assumed in this dissertation that such market-wide volatility does not have a direct and systematic impact on characteristic trading. Thus, one could expect that any significant market-wide herding as a result of extreme states of market-wide volatility manifests primarily from intent.

### *2.3.3 Correlated signals (investigative herding) argument*

Investigative herding is said to result from the process by which information is incorporated into prices (Choi & Sias, 2009). By receiving and acting on information at different times, market participants may exhibit correlated trading activity, and hence generate the impression of herding behaviour, yet is simply as a result of following similar market signals (e.g., analyst

recommendations (Brown et al., (2014)) or as result of preferences for shares with certain characteristics (e.g., shares with high past returns (Grinblatt et al., 1995; and Wermers, 1999), share size (market capitalization), or book-to-market ratio (Wermers, 1999; Barberis & Shleifer, 2003; and Choi & Sias, 2009)). Therefore, the correlation between institutional demand and security prices may not necessarily imply true herding behaviour.

There is, however, a body of empirical research that find contrary explanations for such correlated patterns. A number of studies (e.g., Sias et al., 2006; Froot & Teo, 2008; Kaniel et al., 2008; and Campbell et al., 2009) offer alternative explanations that suggests that herding may drive prices away from fundamentals rather than reflect the process by which information is incorporated into prices (i.e., refuting the correlated signals argument). Dasgupta et al. (2011a) found evidence in favour of this alternative argument where securities persistently purchased by institutions underperformed those persistently sold by institutions (i.e., there was apparent mispricing of securities which induced subsequent price reversals).

Choi & Sias (2009) proposed a method for differentiating the correlated signals argument from the alternatives. In order to satisfy the correlated signals argument, the logic of such testing required that institutional demand be positively correlated to contemporaneous share returns, and not inversely related to subsequent returns. Put simply, under the assumption that asset prices and returns should reflect all available fundamental information (i.e., strong-form efficiency), one would expect a correlation between same-quarter institutional demand and share prices, and subsequent price-reversals should not occur as a result of investigative herding. Analogously, if institutional demand was positively correlated to contemporaneous share returns, and inversely related to subsequent share returns, then such herding is *not* merely reflective of the process by which information is incorporated into share prices. Sias (2004) demonstrated that institutional demand in the US market is more strongly related to lag industry demand than lag returns, refuting the argument presented earlier that correlated trading activity is primarily driven by momentum trading (e.g., Grinblatt et al., 1995; Wermers, 1999; and Jones et al., 1999). Choi & Sias (2009) found evidence consistent with the hypothesis that institutional industry demand impacts prices (i.e., refuting the correlated signals argument). However, Choi & Sias (2009) found only weak evidence that institutional herding drives prices away from their fundamental values (i.e., evidence of return reversals was weak) and concluded that correlated signals *primarily* drive institutional herding.

Popescu and Xu (2014, 2018) controlled for certain style investing effects by examining the cross-sectional regression of unit trust demand on lag demand, lag returns, share size, and share book-to-market ratio. They deduced that, if professional fund managers have a style preference (e.g., shares with high past returns, certain size, or book-to-market ratio), then the cross-correlation (herding measure) should be more pronounced when regressing on these additional factors. Their results revealed that US unit trust demand was positively correlated with lag book-to-market ratio, indicating that the sample funds showed value-investing tendencies, yet the extent of the herding measure (cross-correlation regression) was not significantly influenced by the additional variables. They concluded that unit trusts exhibit herding to a greater extent in down markets than in up markets, even after controlling for the combined effects of lag returns, lag market cap, and lag book-to-market ratio.

#### *2.3.4 Herding by share size*

Previous empirical research has observed that share size may be a key determinant of herding behaviour, with the effect primarily encountered among shares of the smallest (e.g., Lakonishok et al., 1992; Wermers, 1999; Sias, 2004; Wylie, 2005; Hung et al., 2010; and Guney et al., 2017) and largest (e.g., Wylie, 2005; and Kremer & Nautz, 2013) capitalization segments.

As previously mentioned, limited information transparency, for whatever reason, may lead to intentional herding behaviour as investors attempt to resolve this ambiguity by following the trades of their peers<sup>10</sup>. In the case of small capitalization shares with limited analyst following and less informational content relative to larger capitalization shares, an investor may opt to monitor and trade on the information presented by their peers who may be perceived to be better informed (Guney et al., 2017). Moreover, since smaller capitalization shares may suffer low trade volume and liquidity, investors may be motivated to trade smaller capitalization shares with their peers as this collated trading may increase trade volume, reduce trade friction, and ultimately allow their orders to be timely executed (Sias, 2004; and Guney et al., 2017). Sias (2004) also contends that institutional investors may fear such liquidity premium (trading costs) and accumulate or dispose of securities positions over time rather than with single large

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<sup>10</sup> See earlier arguments relating to results of herding being stronger in emerging markets as well as increased market volatility, both of which are characterised by limited information transparency (increased information ambiguity).

orders – this may, in turn, generate the impression of herding as a result of funds following their own lag trades.

Alternatively, investors may herd towards larger capitalization shares due to regulatory or fund mandate restrictions<sup>11</sup>, and may also engage in “benchmark herding” whereby fund managers bias the composition of their portfolios towards the constituent shares of an index against which the fund’s performance is benchmarked in order to avoid underperforming such index (Walter & Weber, 2006). Walter & Weber (2006) further noted that so-called “blue-chip” (i.e., largest capitalization) indices represent the most popular benchmarks against which fund performance is assessed, and hence motivates fund managers to bias their portfolio selection towards larger capitalization shares.

In line with recent studies (Holmes et al., 2013; Gavriilidis et al., 2013; Popescu & Xu, 2014; Economou et al., 2015; and Popescu & Xu, 2018) this dissertation investigated the motivations for herding behaviour by examining the significance of the Sias herding measure under varying market states relating to market returns performance and the level of market volatility. This dissertation extends the empirical analysis to share-size to further investigate whether reputational and/or informational payoffs promote equity unit trust herding in shares.

This dissertation considers the null hypothesis of unintentional herding throughout this paper, and analogously that the extent (level) of herding measure does not vary significantly under different market states.

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<sup>11</sup> For example, Regulation 28 of the Pension Funds Act (1956) of South Africa imposes restrictions on local pension funds with respect to investing in illiquid (or small capitalization) equity shares (e.g., only 5% of total fund value can be invested in shares with total issuer market capitalization of R2 billion) (National Treasury, 2011). Further evidence was presented by Voronkova & Bohl (2005) and Olivares (2008) relating to pension funds in emerging markets that face regulatory restrictions in share-selection, leading to portfolio weighted bias towards the largest capitalization shares in the local (emerging) market.

## Chapter 3: Methodology and Data

This section sets out the methodology and data used to examine the extent and causes of South African equity unit trust herding. Specifically, this dissertation employs the micro-herding measure first developed by Sias (2004) (hereafter the *Sias measure*) and analysed equity unit trust holdings data at the quarterly frequency.

### 3.1 Existing herding measures

The Sias measure has gained prevalence in more recent international herding studies which found strong evidence of herding by institutions in individual shares and within industries (e.g., Puckett & Yan, 2008; Choi & Sias, 2009; Dasgupta et al., 2011a,b; Foster et al., 2011; Holmes et al., 2013; Gavriilidis et al., 2013; and Celiker et al., 2015), while a number of these studies were conducted in context of small to mid-tier emerging economies (e.g., Portugal (Holmes et al., 2013) and Spain (Gavriilidis et al., 2013)), and hence provides a basis for comparability to the results of this dissertation<sup>12</sup>. The Sias measure is also inherently intuitive as a herding measure as it measures correlation in trading activity *across* adjacent periods and thus provides a logical connection with the definition of herding mentioned earlier in this paper (chapter 2.1).

Another micro-herding measure<sup>13</sup>, initially designed by Lakonishok et al. (1992) (hereafter the *LSV measure*) was commonly used and adapted to a number of international herding studies (e.g., Grinblatt et al., 1995; Jones et al., 1999; Wermers, 1999; Wylie, 2005; Walter & Weber, 2006; Celiker et al., 2015; and Abrahamson, 2017). The LSV measure gauges the tendency of trades to accumulate on the same side of the market relative to other independent trades during a given period (Walter & Weber, 2006)<sup>14</sup>. Funds are considered to exhibit herding behaviour if there are significant imbalances between the number of buyers and sellers of a specific investment (Spyrou, 2013). The LSV measure has well-documented shortcomings, specifically

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<sup>12</sup> South African listed equity market fits within middle-tier category, with market capitalisation on JSE Limited of R17,548 billion (USD 1,228 billion) as at 27 December 2019 (JSE Limited, 2020b), comparable to the study conducted by Gavriilidis et al. (2013) in Spain of USD 1,031 billion by year-end 2011. Previous institutional herding studies have widely focused on large capital markets (e.g., US, UK, and Germany) and several small capital markets (e.g., Chile, Poland, and Portugal), while few studies have explored the middle-tier category (e.g., Spain, South Korea, and Taiwan).

<sup>13</sup> Other studies have also examined market-wide herding using alternative macro-herding measures (e.g., Christie & Huang, 1995; Chang et al., 2000; Hwang & Salmon, 2004; Chiang & Zheng, 2010; and Guney et al., 2017).

<sup>14</sup> See Lakonishok et al. (1992) for a further detailed explanation of the LSV measure.

in the context of measuring and characterising intentional herding, and, as a result, has not been used in this dissertation.

*Shortcomings of the LSV measure:*

Bikhchandani & Sharma (2000) argue that the LSV measure cannot differentiate between intentional and unintentional herding since the measure purely detects synchronous trading activity irrespective of the reasons underlying such behaviour. Nonetheless, Walter & Weber (2006) contend that this drawback is not unique to the LSV measure but applies to all such pure statistical devices designed for measuring herding, including the Sias measure.

In addition, the LSV measure documents herding at specific points in time using snapshots of holding data and, through comparison of the quarterly trade imbalances, is also able to detect whether herding in a particular share persists over time. However, the measure is unable to indicate whether it is the same funds that continue to herd (Bikhchandani & Sharma, 2000). Therefore, herding may not be detected across quarters where there are only a few unit trusts following the trades of other funds, and one is also unable to distinguish herding due to investors following their own lag demand from that of following the trading actions of others. This distinction has important implications for examining the underlying composition of herds (i.e., whether the herding behaviour is intentional or spurious). This dissertation accounts for this drawback in the Sias measure, described later.

While the LSV measure accounts for the contemporaneous number of buyers and sellers in a given security, the measure does not directly examine the cross-sectional temporal dependence of trading patterns (Puckett & Yan, 2008). In other words, while both the LSV and Sias herding measures gauge herding over time, the Sias measure allows researchers to detect whether herding behaviour persists for a specific share as well as in the aggregate industry, whereas the LSV measure only accommodates the latter. Moreover, the LSV measure only indirectly captures the temporal nature of herding by testing whether investors *follow* other investors within the *same quarter* (Choi and Sias, 2009).

Finally, the calculation of the LSV measure assumes a binomial distribution for  $B_{k,t}$  (see Eq. (1) later), yet the distribution is actually left truncated given short-selling legal restrictions imposed on certain institutional investors (Wylie, 2005; and Walter & Weber, 2006). The reason for this is that sell-side herding may be limited by short-selling restrictions resulting in a greater tendency for funds to buy in herds which infers a skewed probability distribution for

$B_{k,t}$ . Further, the propensity of all unit trusts to buy a share may, at a minimum, be conditioned on both the size of the fund's initial holdings and their net fund flows (Walter & Weber, 2006). Hence the assumption of  $B_{k,t}$  following a binomial distribution is flawed. Wylie (2005) concludes that the LSV measure may, in turn, be biased in measuring herding when only a small number of fund managers trade. Holmes et al. (2013) argued that the Sias measure is thus more appropriate in measuring herding within a concentrated market as it accounts for this low trade bias.

*Shortcomings of the Sias measure:*

As described by Hsieh (2013) herding is the tendency of investors to accumulate on the same side of the market or to follow the lead of others when they trade. Therefore, theoretical research demands that at least two fund managers trade in the same direction to be classified as herding. Further, Wermers (1999) argues that only a few fund managers trading in the same direction could not be considered a herd. The Sias measure may perceive herding even when one institutional investor follows their own lag and may therefore detect herding when there is none. Various studies in the US (e.g., Sias, 2004; Puckett & Yan, 2008; and Brown et al., 2014) accounted for this shortcoming by filtering their dataset for at least five funds trading to observe true herding. Given the market size in South Africa and number of funds in the equity unit trust dataset, this dissertation examines the extent of herding across time and with different group of funds sizes, conditional on at least one, three, and five funds trading a share, respectively (similar to the study by Holmes et al. (2013) in context of the smaller Portuguese market) – refer to Table 3 presented later. Provided that the extent of herding increases with larger fund group size with respect to specific share trades, one can conclude that the herding result is robust (i.e., the contribution to the aggregate herding measure is accounted for by more than one fund trading). Holmes et al. (2013) reported the portion of the Sias measure relating to funds following others' trades for each of these sample limitations, noting that the extent of herding increased (i.e., contribution to the aggregate cross-correlation across the sample increased) significantly in the third category ( $\geq 5$  funds) compared to that in the first category ( $\geq 1$  fund), providing strong evidence of funds following the trades of their peers.

*Reconciling the strength of the two measures:*

The Sias measure tests for the correlation of demand in consecutive quarters – i.e., it focusses on whether those shares that the greatest demand (or supply) last quarter have the greatest demand (supply) this quarter (Choi & Sias, 2009). On the other hand, the LSV measure

evaluates the average tendency of *every* share in *every* quarter to accumulate on the same side of the market. Therefore, the Sias measure may pick up strong evidence of herding if the fund demand for a few shares are strongly correlated even if the net demand across the remaining shares is near zero. The LSV measure may indeed capture such herding, although the *average* measure across all shares will be relatively small (Choi & Sias, 2009). A few, yet significant share herding observations may therefore be lost in the process of aggregating the LSV herding measure across all shares for the quarter. As a result, Sias (2004) concludes that the different findings in earlier studies compared to their paper result from differences in methodology, rather than differences in nature of the sample selection.

### ***3.2 The Sias measure***

The Sias measure computes the cross-sectional correlation between investors' demand for a given share in consecutive quarters. Sias (2004) exploited the idea that herding implies that fund managers follow each other into or out of equity positions (Puckett & Yan, 2008). Hence, herding occurs where the trading patterns of investors across consecutive quarters are positively correlated. However, this positive cross-correlation may arise from either unit trusts following their own lag across quarters, or unit trusts following the lag of *other* funds across quarters. The former case is not considered intentional (true) herding in the context of this dissertation.

Unit trust demand is defined in this paper as the proportion of unit trusts buying a specific share to the total number of unit trusts trading that specific share in a given quarter. Intuitively, not all market participants can herd together since there has to be both a buyer and a seller in every transaction. Therefore, one can only gauge herding behaviour when investors are examined within homogenous subgroups, such as at the industry or individual share level. This dissertation employed the Sias measure to gauge the average tendency of South African equity unit trusts to accumulate on the same side of the market in a particular share (i.e., at the individual share level) across quarters, relative to what could be expected if those funds traded independently.

This dissertation first defines raw share demand ( $Raw\Delta_{k,t}$ ), identical to that first derived in Lakonishok et al. (1992) and later used by Sias (2004), as the raw fraction of institutions buying a particular share  $k$  in a given quarter  $t$  (share-quarter  $k,t$ ):

$$Raw\Delta_{k,t} = \frac{B_{k,t}}{B_{k,t} + S_{k,t}}, \quad (1)$$

where  $B_{k,t}$  ( $S_{k,t}$ ) denotes the number of unit trusts that increase (decrease) their net holdings in a particular share  $k$  in a given quarter  $t$ . One can interpret a value of  $Raw\Delta_{k,t}$  exceeding 0.5 as a proportionately higher number of net buyers than net sellers of share  $k$  in quarter  $t$ . To allow for aggregation over time and to directly compare coefficients of independent variables in the study, Sias (2004)<sup>15</sup> standardised this equation such that both the dependent and independent variables have zero mean and unit variance, as follows:

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

where  $\overline{Raw\Delta_{k,t}}$  is the cross-sectional average raw demand in quarter  $t$  across  $K$  shares, and  $\sigma(Raw\Delta_{k,t})$  is the cross-sectional standard deviation of the raw demand in quarter  $t$  across  $K$  shares.  $\overline{Raw\Delta_{k,t}}$  is a mean market adjustment factor that controls for aggregate purchasing activity owing to net fund flows in quarter  $t$ . The logic follows that, in periods where unit trusts experience higher net fund inflows, one can reasonably expect a larger number of net buyers overall; for example, in an economic boom where individual investors contribute more to unit trusts, those funds will tend to purchase more than they sell, resulting in a spurious market-wide buy-herd (Walter & Weber, 2006). Therefore, to control for net fund flows  $\overline{Raw\Delta_{k,t}}$  is subtracted from  $Raw\Delta_{k,t}$ <sup>16</sup>. This dissertation defines  $\overline{Raw\Delta_{k,t}}$  as the cross sectional average of the proportion of net buyers across all shares ( $K$ ) in all industries in quarter  $t$ . Put simply,  $\overline{Raw\Delta_{k,t}}$  measures the proportion of net buyers one could expect, on average, to trade independently of other unit trusts in a given quarter (Walter & Weber, 2006).

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<sup>15</sup> Full details of the model and its proof can be found in Sias (2004). For consistency, we use the same terminology.

<sup>16</sup> As previously mentioned, this dissertation also accounts for net fund flows by examining changes in unit trust portfolio weights (i.e., fractional share ownership, holding share prices constant) rather than changes in absolute share positions; an approach that has been adopted in a number of previous herding studies (e.g., Choi & Sias, 2009).

The cross-sectional regression statistic is then estimated for each quarter:

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

where  $\Delta_{k,t-1}$  is the lagged value of the standardised fraction of institutions buying a particular share  $k$  and  $\varepsilon_{k,t}$  is a zero mean error term<sup>17</sup>. Since this standardised regression equation ( $\Delta_{k,t}$ ) has a single independent variable, the regression coefficient ( $\beta_t$ ) is also the cross-sectional correlation between unit trust demand and lagged unit trust demand. i.e., the coefficient  $\beta_t$  measures the cross-sectional correlation between institutional demand this period and last period, and thus serves as an estimate of the extent to which unit trusts in one quarter follow the actions of unit trusts in the previous quarter. However, since a positive cross-correlation (i.e.,  $\beta_t > 0$ ) can be observed through unit trusts repeating their own trades in consecutive quarters, Sias (2004) adjusted  $\beta_t$  to discard this non-herding influence. Hence, this dissertation segregated  $\beta_t$  into two terms:

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

The first (multiplicative) term on the right-hand side of Eq. (4) represents the contribution to the cross-correlation of unit trusts following their own lag demand and the second (multiplicative) term is the contribution of unit trusts following the lag demand of other funds (i.e., unit trust  $n$  following fund  $m$ 's lag demand for share  $k$ ).  $D_{n,k,t}$  is a dummy variable that takes the value of 1 (0) if fund  $n$  buys (sells) share  $k$  in quarter  $t$ , while  $N_{k,t}$  is the number of unit trusts trading share  $k$  in quarter  $t$  (Choi & Sias, 2009; and Celiker et al., 2015).

The second (multiplicative) term will be positive if institutional investors tend to follow each other into and out of the same shares, i.e., if unit trust  $m$  buys (sells) share  $k$  in quarter  $t-1$  and fund  $n$  buys (sells) security  $k$  in quarter  $t$ , the second term will be positive. Conversely, if unit trusts tend to abandon (accumulate) shares that other funds purchased (sold) the previous

<sup>17</sup> The intercept of the regression is zero since both the dependent and independent variables in the regression are rescaled to zero mean (Sias, 2004).

quarter, this term will be negative. This term will be zero if unit trusts' transactions this quarter are independent of other unit trusts' transactions last quarter (Sias, 2004).

To examine the propensity of unit trusts to buy or sell in herds (i.e., the propensity of funds to follow each other into or out of the same shares), cross-correlation coefficient  $\beta_t$  is partitioned for shares that experienced either buy-side or sell-side herding in each quarter. The portion of the cross-correlation arising from funds following each other into (out of) the same share is identified where  $Raw\Delta_{k,t} > 0.5$  ( $Raw\Delta_{k,t} < 0.5$ ).

This dissertation used Eq. (4) to first calculate the average cross-correlation coefficient for each share-quarter within the sample of unit trusts for the entire period under examination (December 2012 – March 2020). This dissertation then adopted the approach of determining herding intent first proposed by Holmes et al. (2013) by gauging the interaction of this cross-correlation coefficient ( $\beta_t$ ) under conditions of varying market-wide states. This dissertation examined the presence of herding intent conditioned upon two variables: market-wide returns and market-wide volatility.

As previously mentioned, this dissertation considered the null hypothesis of unintentional herding throughout this paper. For the first test, this dissertation formally set the null ( $H_0$ ) and alternative ( $H_1$ ) hypotheses as follows:

$H_0$ : South African equity unit trusts do not herd in shares.

$H_1$ : South African equity unit trusts herd in shares.

Under  $H_0$ , the hypothesised mean cross-correlation coefficient ( $\beta_t$ ) would not differ from zero.

### *3.2.1 Methodology – market returns*

As mentioned previously, herding studies have found mixed evidence of herding under conditions of increasing/high or decreasing/low states of market returns. While the directional interaction is ambiguous based on prior studies, this dissertation hypothesizes that the incentive to herd, arising from the reputational cost of deviating from the herd, is much higher in bear markets than in bull markets, for a few reasons. First, the theoretical propositions of reputational herding in the event of down markets is more persuasive than those in up markets – i.e., there are asymmetric reputational/career costs in bull and bear markets, respectively. By analogy, in up markets, in event of herd success, the cost of deviating from the herd may be a

decrease in compensation in most cases, and job loss in some cases (Chevalier and Ellison, 1999; and Popescu & Xu, 2014); yet, in down markets, in event of herd success, the cost of deviating from the herd may be job loss and/or reputational ruin in most cases (Chevalier and Ellison, 1999; Kempf et al., 2009; and Popescu & Xu, 2014). The latter case is more evident when aggregate fund flows to unit trusts decrease in down markets relative to up markets (Popescu & Xu, 2018). Second, while the theoretical concept of herding is largely consistent across the body of literature, the methodological differences in measuring herding may result in a different outcome or conclusion (see, for example, the outcome of Walter & Weber (2006) which employed the LSV measure is different to the outcome of Popescu & Xu (2014, 2018) which employed the Sias measure, notwithstanding that both studies attempted to measure the extent of herding under different market-return states). This dissertation employed the Sias measure which is methodologically similar to other studies that presented evidence of reputational herding being more pronounced in bear markets (e.g., Holmes et al., 2013; Gavriilidis et al., 2013; Popescu & Xu, 2014; and Popescu & Xu, 2018). Finally, by pure count, most studies (mentioned previously) have presented evidence of reputational herding being more pronounced in bear markets. Given the above, this dissertation hypothesized that the extent of herding arising from intent would increase with varying market return-states and be more pronounced in the case of bear markets than in bull markets (H<sub>3</sub>).

For herding to be considered intentional, one would expect herding behaviour to interact with market returns due to reputational and/or information payoffs. In particular, during a down (bear) market, one could expect fund managers (especially poor-quality managers<sup>18</sup>) to follow the trades of their peers in an attempt to (at least) match the performance of their peers while avoiding potential scrutiny for contrarian behaviour during periods of poor fund returns. In an up (bull) market, one could expect similar intentional herding behaviour owing to scrutiny of relative fund performance – since “underperforming during periods of rising prices is more easily associated to low ability” (Gavriilidis et al. (2013)). However, for reasons mentioned previously, one would expect that the extent of herding be greater in case of bear than in bull markets.

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<sup>18</sup> Consistent with Gavriilidis et al. (2013), fund managers are assessed as “poor-quality” on the basis of lower returns performance relative to their peers.

Conversely, if fund managers herd spuriously, one would expect no significant differences in herding behaviour during bear and bull periods, respectively. This dissertation distinguished these hypotheses as follows:

H<sub>2</sub>: Herding by South African equity unit trusts is equal across states of the market (i.e., does not interact with market returns;  $\overline{HM}_A - \overline{HM}_B = 0$ );

H<sub>3</sub>: Herding by South African equity unit trusts interacts with states of market returns (i.e.,  $\overline{HM}_A - \overline{HM}_B > 0$ ),

where  $\overline{HM}$  represents the mean Sias herding measure across all quarters within each market state sub-grouping (A or B). To test the interaction between unit trust herding and states of market returns, this dissertation used the quarter-end closing prices of the FTSE/JSE All-Share Index<sup>19</sup> for the December 2012 – March 2020 period, calculated their quarterly log-differenced returns and ranked the return-series of the index in ascending order. Similar to Gavriilidis et al. (2013) and Holmes et al. (2013), this dissertation first determined the Sias measure (cross-correlation coefficient,  $\beta_t$ ) using Eq (4), conditioned on contemporaneous (i.e. same period) absolute index returns, and then separately on market direction (i.e. relative cross-quarter returns) by splitting the return-series into two parts, contingent upon whether a quarter's index returns are positive or negative (i.e. whether the index has risen/declined in quarter  $t$  compared to quarter  $(t-1)$ ) and then split  $\beta_t$  and its two components: funds following their own trades, and funds following the trades of other funds. Since this dissertation is interested in true herding, the sample is limited to share-observations traded by at least three unit trusts. The dissertation then broke up each return-series into three parts, namely “HIGH” (the top third of the index returns), “MID” (the middle third of the index returns) and “LOW” (the bottom third of the index returns) and attributed  $\beta_t$  to each part, respectively. Finally, this dissertation repeats this analysis conditioned on direction of market returns (“UP MARKET” and “DOWN MARKET”) rather than absolute contemporaneous market returns. This dissertation detected differences in herding across market return states using Student's t-test under the null

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<sup>19</sup> The two JSE benchmark indices are the FTSE/JSE All Share Index, covering 99% of market capitalisation, and the FTSE/JSE Top 40 Index which tracks the top listings in a representative spread of sectors (JSE Limited, 2020a). Since the sample of equity unit trusts invest in the full range of small-to-large cap shares on the JSE Limited, the former was considered more suitable for market-wide returns since it captures the full range of equity share performance on the JSE Limited, while the latter only captures the largest 40 shares and is not representative of the investment universe underlying the sample of unit trusts.

hypothesis that the mean herding measures are equal under all market states (i.e.,  $H_2: \overline{HM}_A - \overline{HM}_B = 0$ ). Results of these analyses are presented later in Table 4.

### 3.2.2 Methodology – market volatility

As previously mentioned, the level of market volatility (and hence, performance risk or uncertainty) may impact the extent of intentional herding as market participants attempt to resolve this uncertainty by following the trades of their peers. For instance, in tranquil (less volatile) market states it is easier to distinguish poor from superior quality managers which may drive intentional herding due to reputational concerns. Conversely, in periods of high market volatility, increased risk and uncertainty may drive herding behaviour when fund managers believe their peers to possess superior information (-processing) skills and thus attempt to resolve the uncertainty by following the trades of their peers (Holmes et al., 2013). It is thus hypothesized that, if herding is intentional, herding behaviour will be impacted by the level of market volatility; conversely, if fund managers herd spuriously, one would not expect such a relationship between herding behaviour and the level of market volatility. The formally defined hypotheses areas follows:

H<sub>4</sub>: Herding by South African equity unit trusts is equal across states of the market (i.e., does not interact with market volatility;  $\overline{HM}_A - \overline{HM}_B = 0$ ).

H<sub>5</sub>: Herding by South African equity unit trusts interacts with states of market volatility (i.e.,  $\overline{HM}_A - \overline{HM}_B > 0$ ).

To test the interaction between unit trust herding and states of market volatility, volatility is estimated using the methodology of Schwert (1989) by calculating the quarterly standard deviation of log-differenced daily returns using the daily closing prices of the FTSE/JSE All-Share Index<sup>20</sup> for the December 2012 – March 2020 period. Similar to the approach presented earlier for analysing the interaction of herding with market returns, the Sias measure (cross-correlation coefficient,  $\beta_t$ ) is determined using Eq (4), conditioned on contemporaneous (i.e. same period) absolute volatility, and then separately on relative cross-quarter volatility by splitting the series of volatility estimate observations into two parts, contingent upon whether quarterly volatility estimate has risen or declined across quarters, and then split  $\beta_t$  and its two

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<sup>20</sup> For the same reasons presented earlier for measuring market returns, this dissertation uses the FTSE/JSE All Share Index to determine volatility of market returns.

components: funds following their own trades, and funds following the trades of other funds. The series of volatility estimate observations is then divided into three parts, namely “HIGH” (the top third of the index volatility values), “MID” (the middle third of the index volatility values) and “LOW” (the bottom third of the index volatility values) and attribute  $\beta_i$  into each part, respectively. Finally, this analysis is repeated conditioned on direction of change in market volatility estimates (“INCREASING” and “DECREASING”) rather than absolute contemporaneous market volatility estimates. Differences in herding across market volatility states using Student’s t-test under the null hypothesis that the mean herding measures are equal under all market states (i.e.,  $H_4: \overline{HM}_A - \overline{HM}_B = 0$ ) were detected. Results of these analyses are presented later in Table 5.

### 3.2.3 Methodology – robustness tests

As noted previously, professional unit trusts may exhibit herding tendencies as a mere result of their preference for certain shares (e.g., habit investing) or fund style. Specifically, the variation in unit trust herding across market states could be explained by inherent conformity of fund manager preferences. Following a similar approach to previous studies (e.g., Walter & Weber (2006) and Popescu & Xu (2014, 2018)), the method controlled for these characteristic trading effects by performing a standardized regression of unit trust fractional share-demand on lag quarter demand, as well as lag quarterly share returns, and lag log market capitalization as follows:

$$\Delta_{k,t} = \beta_{1,t} \Delta_{k,t-1} + \beta_{2,t} R_{k,t-1} + \beta_{3,t} \text{Ln}(\text{Mkt Cap})_{k,t-1} + \varepsilon_{k,t}, \quad (4)$$

where  $R_{k,t-1}$  is the return, and  $\text{Ln}(\text{Mkt Cap})$  is the natural log of the average market capitalization for share  $k$  over quarter  $t-1$ . Unlike Walter & Weber (2006) and Popescu & Xu (2014, 2018), this dissertation did not control for book-to-market ratio as the data on equity book-values was not readily available in the fund holdings dataset.

### 3.2.4 Methodology – herding by share size

As previously mentioned, share size has been cited as a key determinant of herding behaviour, notably in the smallest and largest capitalization segments<sup>21</sup>. In the case of small capitalization shares, evidence from previous studies (e.g., Lakonishok et al., 1992; Wermers, 1999; Sias, 2004; Wylie, 2005; Hung et al., 2010; and Guney et al., 2017) suggests that fund managers may opt to follow the trades of their peers in an attempt to resolve inherent information ambiguity and/or increase trade volume and liquidity in order to allow timely execution of trades of smaller capitalization shares – consistent with the reputational and informational payoff (i.e., intentional herding) models. On the other hand, evidence from studies (e.g., Wylie, 2005; and Kremer & Nautz, 2013) also suggest that fund managers may engage in “benchmark herding”, having an inherent preference for constituent shares of “blue-chip” indices, while other institutions may face fund mandate or other regulatory constraints which require them to weight their portfolio towards larger capitalization shares – consistent with spurious herding motives. The models presented in previous studies were adopted and this it was hypothesized that share size has a pronounced impact on unit trust herding behaviour within the smallest and largest capitalization segments. The set of hypotheses are defined as follows:

H<sub>6</sub>: Herding by South African equity unit trusts is not dependent on share-size (smallest and largest).

H<sub>7</sub>: Herding by South African equity unit trusts is dependent on share-size (smallest and largest).

To test the effect of share-size on unit trust herding, the shares in the test population were ranked from smallest to largest capitalization, based on beginning-of-quarter capitalization, while limiting the sample of shares with at least three unit trusts trading in a given quarter. Then the cross-correlation coefficient,  $\beta_t$  (Eq. (4)) – previously calculated for all shares – was partitioned into five distinct groups (i.e., equal quintiles) for each quarter, with an average of 37 number of shares within each quintile. To discern the impact of “benchmark herding”, this dissertation compared the mean herding across the four smallest quintiles (i.e., excluding the largest share quintile alone) to the aggregate herding measure. The largest share quintile was

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<sup>21</sup> This dissertation considered share size based on the beginning-of-quarter market capitalization. Refer to section 4.2.4 for the cross-correlation results relating to five distinct ranked-order groups (quintiles), whereby the bottom and top quintiles were considered to be “small” and “large” share segments, respectively.

excluded as it represents 37 of the top shares by market capitalization in each quarter, and thus serves as a proxy for the main “blue-chip” index on the JSE Limited – FTSE/JSE Top 40 Index JSE (JSE Limited, 2020a).

Similar to the methodology for discerning herding across varying market states, this dissertation detected differences between mean herding within each share size quintile using Student’s t-test under the null hypothesis that the mean herding measure is equal across all quintiles (i.e.,  $H_0: \overline{HM}_{Quintile A} - \overline{HM}_{Quintile B} = 0$ ). Results of these analyses is presented later in chapter 2.4.2 and Table 7.

### **3.3 Data**

#### *3.3.1 Rationale for share vs industry level observations:*

While various studies examined the extent of herding at the individual share and industry level<sup>22</sup>, this dissertation focused on herding of South African equity unit trusts at the individual share level for various reasons. First, Choi & Sias (2009) argued that the same motives for institutional herding hold at least equally well at the share and industry level. Second, the comprehensive dataset comprising the underlying holdings of South African equity unit trusts allows the author of this dissertation to determine herding behaviour within and between industries, as well as between unit trusts managed by the same institutions. Holmes et al. (2013) argue that different funds with the same custodian company may behave differently and therefore it is preferable to examine data on individual funds rather than on the institutional level. This dissertation’s dataset contains unit trusts with predominantly diverse industry holdings which suggests that the results will be less influenced by industry factors. Refer to Table 1 (Panel E) for descriptive statistics, namely the number of active unit trusts with shareholdings split by industry classification. The industry classifications per share were included in the main dataset from FundsData Online<sup>23</sup>, and was based on the Industry Classification Benchmark rules used on the JSE Limited (FTSE Russel, 2020; JSE Limited, 2020d).

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<sup>22</sup> Refer to Table 2 for summary of results from relevant comparable studies.

<sup>23</sup> Refer to section 3.3.3 for source and description of data.

### 3.3.2 Rationale for focus on equity unit trusts

This dissertation focused on equity unit trusts for a few reasons. First, it is well-documented that unit trusts exhibit typical herding tendencies, namely that unit trusts are known to chase certain characteristics (Falkenstein, 1996), mimic the trades of other funds with good performance (Friend et al., 1970), trade due to reputational concerns (Chevalier and Ellison, 1999), and trade on the same new information (Brown et al., 2014).

Second, unit trust holdings data is accessible at the fund level from The Association for Savings & Investments South Africa (“ASISA”), and fund portfolio detail is aggregated by institutions such as FundsData Online<sup>24</sup>. The Collective Investment Schemes Control Act, 2002 (Act No. 45 of 2002) (“CISCA”) introduced a regulation that imposed quarterly reporting requirements on all registered CIS in South Africa from 2003 (CISCA, 2003). As such, publicly available data for institutional holdings are limited to quarterly reports from unit trust managers which provides a snapshot of institutional portfolio holdings at quarterly intervals. Hence, similar to previous studies (e.g., Sias, 2004; Choi & Sias, 2009; Gavriilidis et al., 2013; Popescu & Xu, 2014; Celiker et al., 2015; and Popescu & Xu, 2018), this dissertation examined unit trust holdings data at a quarterly frequency<sup>25</sup>.

Finally, South African equity unit trusts invest in predominantly marketable securities listed on the JSE Limited. Investors in these unit trusts are expected to be diverse, ranging from common retail individuals to sophisticated investors and institutions, allowing diverse public scrutiny of fund performance, pronouncing the impact of herding. Moreover, the nature of the

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<sup>24</sup> Source: <http://www.fundsdata.co.za>

<sup>25</sup> The lack of higher frequency unit trust holdings data poses a potential limitation in the analysis of herding behaviour. As indicated by Wermers (1999) and Sias (2004), since one only observes institutional ownership at quarter-ends, a fund manager that trades (and potentially herds) within quarters are effectively ignored. Although it is possible that some funds also follow the trades of others on shorter intervals, it is not clear how investors could intentionally mimic the trades of others with no such observable source data in South Africa. Sias (2004) suggests that investors may, from experience, whether due to intent or not, follow the trades of others based on analyst recommendations or common investment styles. While this paper does not explore these specific sources of herding, the data allows for the analysis of herding and draw insights into the causes of such behaviour by, for example, controlling for states of the market and share size, which is comparable to various previous studies (mentioned previously). Therefore, it was not considered that this drawback undermined the results or conclusions.

underlying assets (marketable equity securities) promotes free trade between all classes of investors, thereby enhancing the robustness of results of this dissertation.

### *3.3.3 Source and description of data*

This dissertation is based on a comprehensive database covering unit trusts and collective investment schemes (CIS)<sup>26</sup> in South Africa covering the June 2012 – March 2020 period<sup>27</sup>, obtained from FundsData Online. The complete list of JSE listed equity shares was obtained directly from the JSE Limited<sup>28</sup> and included quarter-end (31 March, 30 June, 30 September, and 31 December) price and volume outstanding data across all JSE-listed equity shares for the study period, June 2012 – March 2020.

FundsData Online is an aggregator of funds data reported by South African unit trusts and is used and accepted as a reliable source of funds data for a range of retail and professional clients (including investment institutions). The professional subscription service to FundsData Online composed of quarterly portfolio share-holdings of all unit trusts invested in – amongst others – the South African listed equity market, and provides the following information corresponding to each equity unit trust: an equity fund code, the month-end number of units held in each fund, as well as the asset category, industry classification, security name and month-end closing price for each asset in which the fund is invested. The initial sample data contained, on average, 148 unit trusts which were invested in 240 shares listed on the JSE Limited<sup>29</sup>. A limitation with the

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<sup>26</sup> There are five categories of collective investment schemes (CIS) currently permitted by CISCA: CIS in securities, CIS in property, CIS in participation bonds, retail hedge funds; and qualified investor hedge funds. CIS in securities is the most common scheme (CISCA, 2002). In practice, CIS in securities are housed in unit trust-type schemes – for comparability to other studies, we have used the term “equity unit trust” to mean a category part of CIS in securities.

<sup>27</sup> The study period was limited up to March 2020 and therefore excluded the fund flow effects resulting from the coronavirus (COVID-19) pandemic.

<sup>28</sup> Email communication – mdsupport@jse.co.za, 12 August 2020

<sup>29</sup> This dissertation focusses solely on unit trust holdings invested in equity shares listed on the JSE Limited, Africa’s largest stock exchange (JSE Limited, 2020a). The JSE Limited Equity market contains almost 400 listed companies (and 800 securities) across the Main Board and AltX the latter of which caters for small and medium-sized businesses (JSE Limited, 2020a). The Equity asset category contains the most extensive and complete historical trading data in South African capital markets, based on the history of Johannesburg Stock Exchange (est. 1887) and the Bond Exchange of South Africa (est. 2009), after which these were merged in the JSE Limited (JSE Limited, 2020a). Moreover, South Africa has previously ranked near the top in the world in terms of

dataset was that it only included funds registered with ASISA at a specific point in time when the data was retrieved. While this population includes all funds (active and inactive) registered on 31 March 2020, there are funds that were not observed if they were deregistered in the period before 31 March 2020. The extent of this survivorship bias was considered by comparing the number of ASISA registered funds at the beginning and end of the study period (i.e., 30 June 2012 and 31 March 2020 respectively). On 30 June 2021, ASISA had 951 registered funds with R1.1 trillion total asset value, while this increased to 1,625 funds and R2.3 trillion total asset value by 31 March 2020 (ASISA, 2020). It is apparent that the number of funds and total asset value increased which partly mitigates the effect of possible survivorship bias.

According to ASISA (ASISA, 2020), there were, on average, 1,183 active CISs registered as of 31 March 2020 (after removing fund of funds to avoid double-counting). Of these, 375 funds were classified as equity-holding, 579 as multi-asset, 73 as real estate and 156 as interest bearing. The dataset in this dissertation included all unit trusts registered with ASISA with classification “South African – Equity”, and therefore also included industry-specific unit trusts. There were 287 registered “South African – Equity” unit trusts with ASISA as at 31 March 2020, of which 230 (80%) were classified as “General”, while the remaining 57 unit trusts (20%) in scope were split as follows: Financial (6), Industrial (4), Resources (8), Large Cap (26), Mid & Small Cap (10), and Unclassified (3). This implies that industry-specific unit trusts made up a relatively small portion of the fund sample and such inert bias would not undermine the results of this dissertation across all JSE Listed shares in all industries. Moreover, this dissertation performed robustness tests accounting for market capitalisation and share price performance, which then partly accounts for the remaining bias in the “Large” and “Mid & Small” Cap unit trust classifications.

The population of “South African-Equity” class unit trusts (consisting initially of 287 funds) was pre-processed. First, funds-of-funds were excluded to avoid double-counting of underlying

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regulation of securities exchanges (World Economic Forum, 2017) which contributes to its credibility as a mature capital market within an emerging economy.

The results of an intentional herding study are only reliable if a market participant can witness the trading actions of other investors. As such, transparency is a fundamental condition for intentional herding to exist. Given the sophistication and regulatory oversight of South Africa’s capital markets, it is at least possible that such transparency condition exists within this market, making an intentional herding study possible.

share trades. With this data, all sub-totals and non-equity share asset classes (local cash, foreign cash, local and foreign bonds, equity derivatives, margin accounts, unclassified domestic assets, and domestic money market accounts) were excluded. All remaining securities were labelled as JSE-listed or not JSE-listed equities, to narrow the scope of this dissertation on pure South African equities listed on the main board and AltX of the JSE Limited. By implication, this scope exclusion also removed foreign and private equity holdings, remaining unit trust investments (fund-of-funds), as well as exchange traded products which may attract index funds that are subject to specific restrictions or characteristics and would otherwise distort the measure of true herding<sup>30</sup>.

198 unique unit trusts (on average, 148 per quarter) invested in 361 unique shares (on average, 240 per quarter) remained after applying these initial restrictions. The observation period (June 2012 – March 2020) consisted of 32 share-quarter snapshots. Since this dissertation was interested in *changes* in equity holdings across adjacent quarters rather than quarter-end snapshot data, this dissertation’s measurable herding period consisted of 30 share-quarters between December 2012 and March 2020. Moreover, this dissertation excluded holding data where the portfolio holding weights did not change across quarters. With these final restrictions, the average number of unique unit trusts in this dissertation’s sample decreased from 148 to 146, and average number of unique shares decreased from 240 to 217 per quarter over the 30-quarter observation period.

The 30 share-quarter observations were considered to be sufficiently large to conduct a reliable herding study as this is comparable to other studies (e.g., Abrahamson (2017) and Economou et al. (2015)) and the average number of unit trusts observed was towards the top-end of comparable emerging market studies (see Table 2).

Table 1 provides a summary of descriptive statistics for the data used in this dissertation. In Table 2, the number of observed funds and share-trades in this dissertation is compared to similar herding studies that employed the Sias measure. The number of South African unit trusts (institutions) observed in this dissertation lies on the bottom-end of the range to all comparable international studies, indicating that it is a smaller and more concentrated market. Holmes et al. (2013) note that, in these conditions, investors know more about the trading

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<sup>30</sup> See earlier arguments regarding fund mandate and legal restrictions, as well as “benchmark herding”.

actions of other investors which facilitates a reliable study on herding, and, in particular, whether herding is intentional or not.

Table 1

## Descriptive statistics.

Panel A reports some descriptive statistics of the overall data sample used. For each quarter this dissertation calculated the number of shares traded by at least one, three or five unit trusts (funds), respectively; for each quarter this dissertation also calculated the number of active share-holding positions per quarter. This dissertation restricted the sample observations to those with active trades across consecutive quarters (i.e., only active buys and sells). Panels B and C provide the time series' averages of these restricted sample figures for each year as well as their total average throughout the sample period (December 2012 - March 2020). Panel D reports the mean count of active funds per share for each category of market capitalization based on the JSE classification criteria (JSE Limited, 2020c), being <R1bn ("SMALL CAP"), R1bn-10bn ("MID CAP"), and >R10bn ("LARGE CAP") capitalization segments. Finally, Panel E reports the mean count of active funds per share, categorized by industry based on the Industry Classification Benchmark rules used on the JSE Limited (FTSE Russel, 2020; JSE Limited 2020d).

<i>Panel A: Sample Data</i>										
Number of unique unit trusts	198	Number of share-holding positions	169,989							
Number of unique shares	361	Number of share-quarters	32							
<i>Panel B: Shares' Statistics</i>										
Average number of active shares per quarter traded by:	2012–2020 average	2012	2013	2014	2015	2016	2017	2018	2019	2020
≥1 fund	217	196	195	204	216	227	227	225	229	218
≥3 funds	184	160	164	172	184	194	197	194	192	177
≥5 funds	159	129	141	148	156	167	169	171	169	160
<i>Panel C: Funds' Statistics - by number of funds trading.</i>										
Average number of active share-holding positions per quarter.	2012–2020 average	2012	2013	2014	2015	2016	2017	2018	2019	2020
≥1 fund	4,944	2,843	3,138	3,609	4,151	5,044	5,563	6,198	6,857	7,245
≥3 funds	4,897	2,794	3,091	3,563	4,106	4,999	5,519	6,155	6,803	7,187
≥5 funds	4,811	2,684	3,008	3,481	4,009	4,906	5,424	6,077	6,725	7,127
<i>Panel D: Funds' Statistics - by market capitalization.</i>										
Average number of active share-holding positions per quarter, split by market capitalization.	2012–2020 average	2012	2013	2014	2015	2016	2017	2018	2019	2020
SMALL CAP	97	77	85	98	108	111	83	103	105	69
MID CAP	780	597	589	609	620	829	842	826	1,120	1,064
LARGE CAP	4,067	2,169	2,464	2,903	3,423	4,104	4,638	5,269	5,632	6,112

Table 1 (continued)  
Descriptive statistics.

*Panel E: Funds' Statistics - by industry.*

Average number of active share-holding positions per quarter, split by industry.	2012–2020 average	2012	2013	2014	2015	2016	2017	2018	2019	2020
Technology	139	88	97	108	133	154	186	139	149	221
Telecommunications	187	149	145	155	173	179	199	228	225	239
Health Care	259	171	175	212	256	280	300	298	305	311
Financials	1,138	530	632	802	1,009	1,197	1,294	1,508	1,542	1,662
Real Estate	410	86	154	217	314	433	525	604	657	603
Consumer Discretionary	689	393	407	428	516	764	819	851	1,008	1,118
Consumer Staples	651	339	383	457	529	630	733	869	937	1,044
Industrials	519	425	451	494	489	530	511	596	583	535
Basic Materials	948	662	696	738	726	877	992	1,095	1,444	1,497
Energy	5	-	-	-	4	2	5	12	9	15

## **Chapter 4: Results – Empirical evidence of share herding by South African equity unit trusts**

In this section the empirical evidence of share herding in South African equity unit trusts using the Sias herding measure (Eq. (4)) estimated over the period December 2012 – March 2020 is reviewed. This paper first presented Table 2, showing the aggregate Sias measure results (mean cross-correlation) of this and other studies, partitioned on unit trusts (institutions) following their own lag demand as well as unit trusts (institutions) following the lag demand of others. This dissertation then presented the Sias measure and its partitioned constituents conditioned on at least one, three, and five unit trusts trading in consecutive quarters – Table 3. Next, this dissertation presented the mean Sias measure results conditioned on states of the market, considering returns and volatility independently – Table 4 and 5, respectively – as well as states of the market controlling for “style” (spurious) herding factors – Table 6. Finally, this dissertation presented the mean Sias measure conditioned on share size – Table 7.

### ***4.1 Industry herding – the evidence***

Previous theoretical<sup>31</sup> and empirical herding studies have demonstrated the propensity for unit trusts to herd in shares or industries. The first null hypothesis ( $H_0$ ) of no unit trust herding in shares was tested by employing the Sias measure. For this test, the alternative hypothesis was as follows:

H<sub>1</sub>: South African unit trusts herd in shares.

#### ***4.1.1 Results – aggregated Sias measure***

Table 2 reports the mean levels for the Sias herding measure defined in chapter 3.2 (Eq. (4)) as well as comparable emerging market (Panel B) and developed market (Panel C) studies. As previously mentioned, the Sias measure computes the cross-sectional correlation between investors’ demand for a given share in consecutive quarters. While the Sias measure captures the cross-sectional correlation for *all* institutions (including that of one’s own demand), this dissertation determined intent through observation of the contribution of this measure relating to unit trusts following the demand of *other* institutions. Therefore the total cross-sectional correlation was segregated into two parts; the contribution to cross-correlation from unit trusts

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<sup>31</sup> Refer to chapter 2 of this paper for summation of proposed motives for institutional herding.

following their own lag demand, and unit trusts following the lag demand of other unit trusts. There is evidence of overall herding across institutions, consistent with these international studies. While the aggregate cross-correlation ( $\beta t$ ) result of this dissertation (13.73%) is below the average of the comparable studies in developed markets (26.25%) as well as emerging markets (26.63%), the portion of cross-correlation arising from funds following their own lag demand (8.51%) was above the average across both market sets – emerging (8.32%) and developed (7.25%). In turn, the portion of cross-correlation arising from funds following the lag demand of other funds in this dissertation falls below the average of the comparable international studies. These results are not necessarily indicative that herding is less prevalent in the South African unit trust population relative to the rest of the world, nor is it indicative of the causes of herding behaviour in South Africa relative to the rest of the world. Rather, these results could be a function of factors unique to each study (for example, sample size and level of market focus – security, industry or market level), as well as market factors (for example, information transparency and concentration of the market), which undermines direct comparability across these studies. For example, Economou et al. (2015) focused on highly concentrated markets, with an average of 6 and 25 unit trusts trading across the 8-year study period, while this dissertation observed, on average, 146 unit trusts across 9 years. The observed cross-correlation results of 74.30% and 23.70% in the Economou et al. (2015) study was, on average, distinctly higher than all other comparable studies shown in Table 2.

To ascertain the effect of fund clustering on mutual fund herding in South Africa, this dissertation aggregated the mean Sias measure into three distinct fund size groups; panels A, B, and C of Table 3 present the aggregate and partitioned cross-correlation results, limiting the sample to shares traded by at least one, three and five unit trusts, respectively, including associated *t*-statistics. This dissertation did not partition the cross-correlation results on buy- and sell-side herding as this dissertation was primarily interested in correlated fund activity, regardless of trade direction.

Table 2

Testing results - Mean Sias herding measure - this dissertation and selected comparable studies.

Panel A reports cross-correlation results obtained by applying the Sias measure to the South African equity unit trust industry. The reported cross-correlation coefficient ( $\beta_t$ ) (column 8) was partitioned into the portion of the cross-correlation resulting from institutional investors following their own lag demand (column 9), and the portion resulting from institutions following the lag demand of other institutions (column 10) (see Eq. (4)). All data were standardized (i.e. rescaled to zero mean, unit variance) each quarter. Panels B and C report results of the Sias measure extracted from emerging market and developed market studies, respectively, for comparative purposes. (#) indicates that various institutions (banks, insurance companies, pension funds, unit trusts, independent advisers, endowments, and other institutions) were examined in the respective study.

Comparable herding studies	Time period	Country	Sub-group for focus of herding study	Subject institution	Average number of institutions in study.	Frequency of period observations	Mean average correlation coefficient ( $\beta_t$ )	Institutions following their own lag industry/share demand	Institutions following other institutions' lag industry/share demand
Panel A: Results for this dissertation									
	12-20	South Africa	Equity share level	Unit trusts	156	Quarterly	0.1373	0.0851	0.0522
Panel B: Results for selected emerging markets									
Holmes et al. (2013)	98-05	Portugal	Equity share level	Unit trusts	45	Monthly	0.0424	0.0151	0.0272
Gavriilidis et al. (2013)	95-08	Spain	Industry level	Unit trusts	1543	Quarterly	0.0426	-0.0112	0.0538
Economou et al. (2015)	05-12	Bulgaria	Equity share level	Unit trusts	25	Quarterly	0.2370	-0.0520	0.2890
Economou et al. (2015)	05-12	Montenegro	Equity share level	Unit trusts	6	Quarterly	0.7430	0.3810	0.3620
Panel C: Results for selected developed markets									
Sias (2004)	83-97	USA	Securities level	Various institutions (#)	894	Quarterly	0.1194	0.0617	0.0576
Puckett & Yan (2008)	99-04	USA	Securities level	Various institutions (#)	776	Weekly	0.4040	0.1710	0.2340
Choi & Sias (2009)	83-05	USA	Industry level	Various institutions (#)	692	Quarterly	0.4049	0.0307	0.3743
Popescu & Xu (2014)	83-06	USA	Securities level	Various institutions (#)	1303	Quarterly	0.2617	0.0661	0.1956
Celiker et al. (2015)	80-13	USA	Industry level	Unit trusts	1367	Quarterly	0.2309	0.0591	0.1718
Popescu & Xu (2018)	80-10	USA	Industry level	Unit trusts	692	Quarterly	0.1540	0.0467	0.1073

Table 3

Mean Sias herding measure - controlling for the number of funds trading a given share ( $k$ ) in each quarter ( $t$ ) (share-quarter  $k,t$ ).

Panel A reports mean cross-correlation results ( $\beta t$ ) obtained by applying the Sias measure to the South African unit trust industry for the period December 2012 – March 2020. The reported mean cross-correlation (first column) was partitioned into the portion of the cross-correlation resulting from unit trusts (funds) following their own lag demand (second column), and the portion resulting from unit trusts following the lag demand of other funds (third column) (see Eq. (4)). All data were standardized (i.e., rescaled to zero mean, unit variance) each quarter. Panels B and C reports mean average results of the Sias measure when limiting the sample of shares traded by at least three and five funds respectively. Student's t-statistics are reported in parentheses. \*\* Indicates statistical significance at the 5% level. \*\*\* Indicates statistical significance at the 1% level.

Mean cross-correlation coefficient ( $\beta t$ )	Partitioned cross-correlation		Average Adj. $R^2$
	Funds following their own lag share demand	Funds following other funds' lag share demand	
<i>Panel A: Shares traded by <math>\geq 1</math> fund</i>			
0.1373 (5.88)***	0.0851 (4.57)***	0.0522 (3.74)***	2.95%
<i>Panel B: Shares traded by <math>\geq 3</math> funds</i>			
0.1340 (5.92)***	0.0718 (6.91)***	0.0622 (3.51)***	3.02%
<i>Panel C: Shares traded by <math>\geq 5</math> funds</i>			
0.1397 (6.17)***	0.0672 (9.02)***	0.0725 (3.37)***	2.94%

The results in Table 3 provide the mean aggregate and partitioned cross-correlation results across the 30-quarter sample period. The observed results were positive and significant in all cases, while the portion of cross-correlation from funds following other funds' lag demand was 39% ( $0.0725/0.0522-1$ ) higher for shares traded by at least five funds (Panel C) relative to shares traded by at least one fund (Panel A), which, in combination, provides strong support for the first alternative hypothesis ( $H_1$ ) – i.e. South African unit trusts herd in shares – and therefore the first null hypothesis ( $H_0$ ) that South African equity unit trusts do not herd was rejected. Moreover, the results presented in Table 2 and 3, respectively, reveal that, on average, about 38% of the cross-correlation (i.e.  $0.0522/0.1373$ ) results from unit trusts buying (selling) shares this quarter that were bought (sold) by other unit trusts in the previous quarter (statistically significant at the 1% level). In summary, this research found strong evidence of

correlated trading activity amongst South African equity unit trusts, although a major portion (62%) of this correlation is due to funds following their own trades across adjacent quarters.

This dissertation considers the causes of this trading behaviour: first, by investigating the impact of market states on herding behaviour, and second, by controlling for certain style strategies that may induce spurious correlated trading activity.

#### ***4.2 Industry herding – analysis of the causes***

Given the findings that share-herding took place in the aggregate equity market over the period investigated, the arguments presented earlier relating to *why* unit trust managers herd (i.e., whether motivated by intent or not) were considered. First, the market returns approach (discussed in chapter 2.3.1) was considered, and then the market volatility approach (discussed in chapter 2.3.2) was used to investigate the potential sources of such herding behaviour.

##### *4.2.1 Results – market returns*

Table 4 presents the aggregate and partitioned cross-correlation results (including associated *t*-statistics) conditional upon states of contemporaneous and direction of quarterly market returns<sup>32</sup>. The observations were limited to trades by at least three funds to filter out correlated activity from one or two funds following their own actions. As mentioned previously, significant differences between the observed sub-groups could indicate that herding is intentional while no differences could suggest that herding is spurious – i.e., not conditional on market returns.

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<sup>32</sup> Given 30 total quarterly observations, we allocate 10 observations to each of the “HIGH”, “MID”, and “LOW” market return groups. There were 12 observations relating to “UP” market return groups and 18 observations relating to “DOWN” market return groups. Refer to the appendix for summary of market returns and volatility across the sample period.

Table 4

Mean Sias herding measure - controlling for market returns ( $\geq 3$  unit trust managers).

The dissertation reports cross-correlation results obtained by applying the Sias measure to the South African unit trust industry for the period December 2012 – March 2020, limiting the sample of shares traded by at least three unit trusts (funds). The reported mean cross-correlation (second column) was partitioned into the portion of the cross-correlation resulting from unit trusts following their own lag demand (third column), and the portion resulting from unit trusts following the lag demand of other funds (fourth column) (see Eq. (4)). All data are standardized (i.e., rescaled to zero mean, unit variance) each quarter. Panel A reports the mean cross-correlation ( $\beta_t$ ) based on three distinct groups of contemporaneous market return levels ("HIGH", "MID", and "LOW"), with 10 observations in each category. The three distinct groups of market returns were determined based on top third ("HIGH"), middle third ("MID"), and bottom third ("LOW") of the sample period's market returns, being the log-differenced returns based on quarter-end closing prices of the FTSE/JSE All-Share Index for the December 2012 – March 2020 period, ranked in ascending order. Panel B reports the partitioned mean cross-correlation ( $\beta_t$ ) based on two sub-groupings ("UP MARKET" and "DOWN MARKET") contingent upon whether the market index was increasing or decreasing across quarters, respectively. A fund was defined as increasing (decreasing) its position in a share if it held a greater (lesser) fraction of the firm's shares at the end of the quarter than it held at the beginning of the quarter. Figures in parentheses represent Student's t-statistics corresponding to each correlation result, and the cross-sectional average t-test for differences between means is reported in the final row of each panel.

\*\* Indicates statistical significance at the 5% level. \*\*\* Indicates statistical significance at the 1% level.

	Mean cross-correlation coefficient ( $\beta_t$ )	Partitioned cross-correlation		Average Adj. R <sup>2</sup>
		Funds following their own lag share demand	Funds following other funds' lag share demand	
<i>Panel A: Market returns (HIGH-MID-LOW)</i>				
HIGH	0.1033 (2.18)**	0.0745 (2.07)**	0.0288 (0.80)	2.73%
MID	0.1585 (4.10)**	0.0752 (5.18)**	0.0833 (2.58)**	3.77%
LOW	0.1402 (4.36)***	0.0657 (4.07)***	0.0744 (2.52)**	2.55%
<i>T-test for differences</i>	(0.64)	(0.22)	(0.77)	
<i>Panel B: Market direction (UP and DOWN MARKET).</i>				
UP MARKET	0.1204 (3.13)***	0.0813 (4.46)***	0.0391 (1.49)	2.93%
DOWN MARKET	0.1430 (5.04)***	0.0655 (5.21)***	0.0775 (3.27)***	3.07%
<i>T-test for differences</i>	(0.47)	(0.71)	(1.09)	

The results reveal strong evidence of aggregate herding across all market return states (significant at the 5% level), while this behaviour is only partly explained by unit trusts following the trades of other unit trusts – on average across all market-return states, about 46% (0.0606/0.1331) of the total cross-correlation is explained by funds following other funds' lag share demand. Moreover, the tests for differences of coefficients (t-test for differences) are not significant indicating that aggregate herding does not interact with market returns.

Since overall cross-correlation results presented in Table 4 is significant across all states of the market and the coefficients are not different from each other, it is observed that the level of market returns does not influence overall herding activity. This is consistent with earlier arguments, namely that the relative homogeneity of fund managers (educational backgrounds and experience) as a group is not expected to change significantly across quarters – nor under different market states (Holmes et al., 2013; and Gavriilidis et al., 2013) – and one would expect fund managers to react to the performance of individual shares rather than the market as a whole, *ceteris paribus*.

The results of the overall Sias herding measure (column 2) in Table 4 also reveal that the propensity of unit trusts to herd is approximately 36% (0.1402/0.1033-1) higher in states of LOW relative to HIGH market return states, and approximately 19% (0.1430/0.1204-1) higher in DOWN markets relative to UP markets. Moreover, the cross-correlation result from funds following their own lag trades (column 3) is significant across all market-return states, yet not significantly different from each other, indicating that such spurious herding does not interact with the level of market returns.

The portion of the overall results in each market return state that is explained by unit trusts following the trades of others is only significantly different from zero in states of LOW and MID market returns and in DOWN markets (at about 53% of the average cross-correlation). Moreover, by measure of the increased adjusted R-squared value, the results reveal that, on average, herding behaviour is partly driven by the state of the market, that herding behaviour increases during bear markets. These findings are consistent with other studies (e.g., Portugal – Holmes et al. (2013); Spain – Gavriilidis et al. (2013); and USA – Popescu & Xu (2014 & 2018)) but is inconsistent with the results of Walter & Weber (2006) who presented evidence of significantly stronger herding tendencies in bull over bear markets – although, this difference could be explained by the methodological differences whereby Walter & Weber (2006) used the LSV measure to gauge industry herding in German mutual funds. As mentioned in chapter

2, the tendency to intentionally herd is expected to be more pronounced in down markets than in up markets owing to asymmetric reputational and career costs of fund managers. As such, the results presented in Table 4 highlight findings consistent with these studies and the reputational herding hypothesis – particularly, the portion of cross-correlation owing to funds following the trades of other funds (column 4) is more weighted and significant in LOW and MID market return states and in DOWN markets. However, these differences across market states are not significantly different from each other (p-value = 0.150), indicating that, although the correlation estimate is more pronounced in bear over bull markets, this dissertation does not find conclusive evidence that such herding interacts with market returns. The author of this dissertation therefore fails to reject the 2nd null hypothesis ( $H_2$ ) that herding interacts with the level and/or direction of market returns.

#### *4.2.2 Results – market volatility*

Table 5 presents the aggregate and partitioned cross-correlation results (including associated  $t$ -statistics) conditional upon states of contemporaneous and direction of quarterly market volatility estimates<sup>33</sup>. Analogous with earlier arguments, significant differences between the observed sub-groups of market volatility could indicate that herding is intentional while no differences could suggest that herding is spurious – i.e., not conditional on the level or direction of market volatility.

Arranging the cross-correlation results into market volatility groups reveals similar evidence to market return groups. Overall herding behaviour is consistent and significant across all market volatility states at the 5% level. These results are also consistent with spurious herding arguments, namely that spurious herding activity is not expected to be driven by states of the market due to homogeneity in the make-up of fund managers and the propensity to react to risk (volatility) of the individual shares rather than the market as a whole.

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<sup>33</sup> Given 30 total quarterly observations, 10 observations were allocated to each of the “HIGH”, “MID”, and “LOW” market volatility groups. There were 11 observations relating to “INCREASING” market volatility and 19 observations relating to “DECREASING” market volatility groups. Refer to the appendix for summary of market returns and volatility across the sample period.

Table 5

Mean Sias herding measure - controlling for market volatility ( $\geq 3$  unit trust managers).

This dissertation reports cross-correlation results obtained by applying the Sias measure to the South African unit trust industry for the period December 2012 – March 2020, limiting the sample of shares traded by at least three unit trusts (funds). The reported mean cross-correlation coefficient ( $\beta_t$ ) (second column) was partitioned into the portion of the cross-correlation resulting from unit trusts following their own lag demand (third column), and the portion resulting from unit trusts following the lag demand of other funds (fourth column) (see Eq. (4)). All data were standardized (i.e., rescaled to zero mean, unit variance) each quarter. Panel A reports the mean cross-correlation ( $\beta_t$ ) based on three distinct groups of contemporaneous market volatility levels ("HIGH", "MID", and "LOW"), with 10 observations in each category. The three distinct groups of market volatility were determined based on top third ("HIGH"), middle third ("MID"), and bottom third ("LOW") of the sample period's market volatility estimate observations, ranked in ascending order. Quarterly market volatility was estimated using the Schwert (1989) method, calculating quarterly standard deviation based on log-differenced returns of daily closing prices of the FTSE/JSE All-Share Index for the December 2012 – March 2020 period. Panel B reports the partitioned mean cross-correlation ( $\beta_t$ ) based on two sub-groupings ("INCREASING" and "DECREASING") contingent upon whether the market volatility estimate was increasing or decreasing across quarters, respectively. Figures in parentheses represent Student's t-statistics corresponding to each correlation result, and the cross-sectional average t-test for differences between means is reported in the final row of each panel.

\*\* Indicates statistical significance at the 5% level. \*\*\* Indicates statistical significance at the 1% level.

	Mean cross-correlation coefficient ( $\beta_t$ )	Partitioned cross-correlation		Average Adj. $R^2$
		Funds following their own lag share demand	Funds following other funds' lag share demand	
<i>Panel A: Market volatility (HIGH-MID-LOW)</i>				
HIGH	0.1164 (3.80)***	0.0556 (1.54)	0.0608 (1.69)	2.12%
MID	0.1828 (4.08)***	0.0793 (4.38)***	0.1036 (2.63)**	4.92%
LOW	0.1027 (2.57)**	0.0806 (3.95)***	0.0221 (0.86)	2.01%
<i>T-test for differences</i>	(0.94)	(0.41)	(1.14)	
<i>Panel B: Direction of market volatility (INCEASING and DECREASING).</i>				
INCREASING	0.1654 (4.94)***	0.0648 (3.98)***	0.1007 (3.90)***	3.70%
DECREASING	0.1158 (3.87)***	0.0759 (5.55)***	0.0399 (1.77)**	2.62%
<i>T-test for differences</i>	(1.11)	(0.52)	(1.77)	

The empirical results presented in Table 5 reveal that aggregate herding behaviour is 12% (0.1164/0.1027-1) more prevalent in HIGH relative to LOW, and 30% (0.1654/0.1158-1) more prevalent in INCREASING relative to DECREASING market volatility states. Herding due to following one's own lag trades (column 3) explains most of the cross-correlation – on average, 52% – as well as explicitly for LOW and DECREASING volatility states (78% and 66% respectively), both significant at the 1% level.

On the other hand, herding due to unit trusts following the trades of others (column 4) is more significant in INCREASING and in MID volatility state groups, explaining 61% and 57% of total cross-correlation, significant at the 1% and 5% level, respectively. Moreover, overall correlated activity is better explained in the INCREASING and MID volatility state groups, by measure of the increased adjusted R-squared value. The results are similar when the analysis was conditioned on five, rather than three volatility-state groups – i.e., the correlation from unit trusts following the trades of others was weighted and significant in the middle group rather than the low or high ends.

These results indicate that spurious correlated activity – arising from unit trusts following their own lag demand – is not conditional on states of market volatility. Moreover, correlation from unit trusts following the trades of others is only partly explained by market volatility states – i.e., there is a higher herding propensity in INCREASING relative to DECREASING volatility states, while the correlation within the HIGH and LOW contemporaneous volatility sub-groups are not significant at the 5% level. The t-test for differences reveal that, on average, herding behaviour does not interact with the level of market volatility; however, the difference in correlation from unit trusts following others (column 4) is significant at the 10% level between MID and LOW volatility groups (p-value = 0.058), as well as between the INCREASING and DECREASING volatility groups (p-value = 0.053). The latter results could be explained by the informational herding hypothesis – i.e., during periods of higher (or increasing) market volatility, fund managers (especially poor-quality managers) may seek to resolve their uncertainty by following the trades of their peers due to their perceived superior information (-processing) skills – consistent with Gavriilidis et al. (2013). However, the empirical results in Panel A are inconsistent with the informational herding hypothesis as the propensity to herd is centered around the MID relative to LOW/HIGH volatility groups.

Based on the empirical results of this dissertation, the overall propensity to herd is more pronounced and significantly different between market states within the MID and

INCREASING volatility state groups relative to LOW and DECREASING, respectively. Herding by intent is only partly explained by the direction rather than the contemporaneous state of market volatility. Due to the disparate results of herding arising from unit trusts following others' lag share demand, the author of this dissertation fail to reject the 3rd null hypothesis (H4) that herding behaviour is spurious and does not depend on market volatility. In other words, the results suggest that herding behaviour arising from unit trusts following the trades of others (premised in intent) cannot be explained by market volatility.

#### *4.2.3 Robustness test – “style” investing factors*

Table 6 presents the results from the cross-sectional regressions of unit trust demand on lag unit trust demand, lag quarterly return, and lag log market cap for each pair of consecutive quarters between December 2012 and March 2020, under varying market states (considering separate market returns and market volatility observations).

By including additional regression variables for lag share returns ( $\beta_2$ ) and lag log market capitalization, ( $\beta_3$ ) the R-squared variable increases which indicates that share demand can be better explained with these additional variables. However, the regression coefficients ( $\beta_2$  and  $\beta_3$ ) provide mixed results across the varying market states. Particularly, the coefficient variables are mostly low and inconstant across market states. Moreover, the results on these additional variables are only significant in few of the market state conditions (i.e.,  $\beta_2$  in mid-market returns, high/low and decreasing volatility states, and  $\beta_3$  in up markets as well as mid-and decreasing volatility states). These results indicate that, although the explanatory power of the model increases, the addition of these variables does not provide evidence that characteristic trading dominates herding behaviour. Moreover, the results of lag unit trust demand ( $\beta_1$ ) are consistent with earlier findings; namely, unit trust herding propensity is approximately 35% (0.1439/0.1070-1) more in high relative to low market return states, 20% (0.1477/0.1234-1) higher in down relative to up markets, 12% (0.1179/0.1054-1) more in high relative to low volatility, and 38% (0.1669/0.1212-1) higher in increasing relative to decreasing volatility sub-groupings, all after controlling for the combined effects of lag quarter returns and lag log market cap. Therefore, the results and analyses provided earlier are considered robust after accounting for “style” investing factors.

Table 6

Mean Sias herding measure - controlling for "style" investing under varying market states.

This dissertation reports cross-correlation regression results obtained by applying the Sias measure to the South African unit trust industry for the period December 2012 – March 2020, limiting the sample of shares traded by at least three unit trusts (funds). This dissertation regressed the cross-sectional share-demand on lag unit trust demand ( $\beta_1$ ), lag quarterly return ( $\beta_2$ ), and lag log market cap ( $\beta_3$ ) for each pair of consecutive quarters (see Eq. (4)). All data were standardized (i.e., rescaled to zero mean, unit variance) each quarter. This dissertation reports the overall cross-correlation regression results in Panel A. Panel B reports the cross-correlation regression based on three distinct groups of contemporaneous market return levels ("HIGH RET", "MID RET", and "LOW RET"), with 10 observations in each category. The three distinct groups of market returns were determined based on top third ("HIGH RET"), middle third ("MID RET"), and bottom third ("LOW RET") of the sample period's market returns, being the log-differenced returns based on quarter-end closing prices of the FTSE/JSE All-Share Index for the December 2012 – March 2020 period, ranked in ascending order. Panel C reports the cross-correlation regression based on two sub-groupings ("UP MARKET" and "DOWN MARKET") contingent upon whether the market index was increasing or decreasing across quarters, respectively. A fund was defined as increasing (decreasing) its position in a share if it held a greater (lesser) fraction of the firm's shares at the end of the quarter than it held at the beginning of the quarter. Panel D reports the cross-correlation regression based on three distinct groups of contemporaneous market volatility levels ("HIGH VOL", "MID VOL", and "LOW VOL"), with 10 observations in each category. The three distinct groups of market volatility were determined based on top third ("HIGH VOL"), middle third ("MID VOL"), and bottom third ("LOW VOL") of the sample period's market volatility estimate observations, ranked in ascending order. Quarterly market volatility was estimated using the Schwert (1989) method, calculating quarterly standard deviation based on log-differenced returns of daily closing prices of the FTSE/JSE All-Share Index for the December 2012 – March 2020 period. Finally, Panel E reports the cross-correlation regression based on two sub-groupings ("INCREASING" and "DECREASING") contingent upon whether the market volatility estimate was increasing or decreasing across quarters, respectively. Student's t-statistics are reported in parentheses.

\*\* Indicates statistical significance at the 5% level. \*\*\* Indicates statistical significance at the 1% level.

	$\beta_1$	$\beta_2$	$\beta_3$	Average Adj. R <sup>2</sup>
<i>Panel A: Overall: shares traded by <math>\geq 3</math> funds</i>				
	0.1380 (5.97)***	(0.0804) (1.00)	(0.0023) (1.62)	3.86%
<i>Panel B: Market returns (HIGH-MID-LOW)</i>				
HIGH RET	0.1070 (2.17)**	(0.3439) (9.54)***	(0.0061) (0.17)	4.50%
MID RET	0.1630 (4.15)***	0.0119 (0.09)	(0.0001) (0.05)	4.31%
LOW RET	0.1439 (4.55)***	0.0909 (1.05)	(0.0008) (0.34)	2.75%
<i>Panel C: Market direction (UP and DOWN MARKET)</i>				
UP MARKET	0.1234 (3.16)***	(0.1987) (1.16)	(0.0049) (3.95)***	3.81%
DOWN MARKET	0.1477 (5.08)***	(0.0015) (0.02)	(0.0006) (0.29)	3.89%

Table 6 (continued)  
Mean Sias herding measure - controlling for "style" investing under varying market states.

	$\beta_1$	$\beta_2$	$\beta_3$	Average Adj. R2
<i>Panel D: Market volatility (HIGH-MID-LOW)</i>				
HIGH VOL	0.1179 (3.88)***	0.1262 (3.50)***	0.0013 (0.04)	2.51%
MID VOL	0.1905 (4.07)***	(0.0754) (0.62)	(0.0057) (2.39)**	5.91%
LOW VOL	0.1054 (2.66)**	(0.2919) (1.98)**	(0.0026) (0.88)	3.14%
<i>Panel E: Direction of market volatility (INCEASING and DECREASING)</i>				
INCREASING	0.1669 (5.13)***	0.0973 (0.90)	0.0003 (0.15)	4.06%
DECREASING	0.1212 (3.88)***	(0.1832) (1.74)**	(0.0039) (2.10)**	3.74%

#### *4.2.4 Results – herding by share size*

Table 7 presents the aggregate and partitioned cross-correlation results conditional upon contemporaneous beginning-of-quarter market capitalization (i.e., share size). This dissertation partitioned the average cross-correlation between unit trusts following their own trades and unit trusts following the trades of others, segregated into five distinct groups (quintiles) based on the ranked order beginning-of-quarter market capitalization.

The results in Table 7 reveal overall significant and positive correlation across all share sizes in the observation period – with about 48% of the overall cross-correlation explained by unit trusts following their own lag demand. More explanatory power (by measure of adjusted R-squared) is observed in the extreme quartile ends – Small and Large shares, respectively. Moreover, the contribution to total cross-correlation arising from unit trusts following the trades of others (column 6) was more pronounced and significant in the largest share segment – about 78% (0.1256/0.1607) of total cross-correlation, significant at the 1% level – while the lowest contribution was observed in the smallest share segment – about 9% (0.0129/0.1396) – which is not statistically significant. The correlation due to unit trusts following the trades of others (column 6) within the largest share segment differs from quintile 1 (significant at the 1% level), and quintile 3 and 4 (significant at the 10% level), indicating that unit trusts follow others in large shares – consistent with the findings in Wylie (2005) and Kremer & Nautz (2013).

The t-tests for differences also reveal that overall herding (column 4) is equal across all capitalization quintiles. However, the portion of correlation relating to unit trusts following their own lag trades (column 5) in the Small shares quintile is significantly different from all other capitalization quintiles (average t-statistic of 3.66, corresponding to p-value of 0.002 – i.e., significant at 1% level). This reveals that fund managers tend to follow their own lag trades in smaller capitalization shares.

Table 7

Mean Sias herding measure - controlling for share size ( $\geq 3$  unit trust managers).

This dissertation reports cross-correlation results obtained by applying the Sias measure to the South African unit trust industry for the period December 2012 – March 2020, limiting the sample of shares traded by at least three unit trusts (funds). For each quintile, the study reports the average count of shares (n) (column 2) and average contribution of market capitalization (column 3) in each segment, with the latter expressed as a percentage fraction of the segment's market capitalization to the total sample market capitalization in the lagged sample quarter (t-1). For each quarter, this dissertation determined the mean average cross-correlation ( $\beta_t$ ) across each of capitalization quintiles based on the ranked order beginning-of-quarter market capitalization for the sample period across all sample shares. The reported mean cross-correlation ( $\beta_t$ ) (fourth column) was partitioned into the portion of the cross-correlation resulting from unit trusts following their own lag demand (fifth column), and the portion resulting from unit trusts following the lag demand of other funds (sixth column) (see Eq. (4)). All data were standardized (i.e., rescaled to zero mean, unit variance) each quarter. Figures in parentheses represent Student's t-statistics corresponding to each correlation result, and the cross-sectional average t-test for differences between means is reported in the final row of each panel.

\*\* Indicates statistical significance at the 5% level. \*\*\* Indicates statistical significance at the 1% level.

Capitalization quintile	Count and contribution of sample population		Partitioned cross-correlation			Average Adj. R <sup>2</sup>
	Average count of shares (n)	Average contribution to market capitalization	Mean average correlation coefficient (Eq. (4))	Funds following their own lag share demand	Funds following other funds' lag share demand	
Small shares	36	0.4%	0.1396 (3.75)***	0.1267 (6.36)***	0.0129 (0.44)	4.17%
Quintile 2	37	1.5%	0.1517 (4.41)***	0.0556 (3.47)***	0.0961 (3.16)***	3.08%
Quintile 3	37	3.7%	0.0886 (2.10)**	0.0465 (3.06)***	0.0421 (1.13)	3.16%
Quintile 4	37	10.2%	0.0728 (2.11)**	0.0327 (3.14)***	0.0401 (1.26)	1.08%
Large shares	37	84.1%	0.1607 (3.82)***	0.0351 (8.38)***	0.1256 (3.09)***	5.63%
<i>T-test for differences</i>			(0.89)	(1.92)	(1.17)	
Total	184	100%				

In line with earlier arguments, unit trust managers may herd towards larger capitalization shares due to regulatory or fund mandate restrictions, as well as benchmark herding – consistent with spurious herding motives. Moreover, results in Table 4 revealed that herding behaviour was significant and positive in all market-return states as proxied by the cross-quarter returns of the FTSE/JSE All-Share Index. Although, correlated activity arising from unit trusts following the trades of others was more pronounced in bear markets than in bull markets, which – when drawn with insights of the correlation within market capitalization segments (Table 7) – could be as a result of intentional motives (for example, reputational/cost trade-offs) or due to spurious motives (for example, index-tracking funds following other index-tracking funds).

As observed earlier, “LARGE CAP” shares (Table 1) make up 4,067 (i.e., 82%) of the 4,944-average number of shareholding positions during the 2012-20 sample period. Large shares (Table 7) also dominate the percentage contribution to market capitalization in this dissertation. To account for the possible bias towards “blue-chip” shares, this dissertation controlled for benchmark herding by comparing the mean herding measure for all shares against the mean herding measures for the smallest four share quintiles (i.e. Small shares, Quintile 2, 3, and 4). When excluding the Large shares quintile from the results, the mean herding measure does not differ from the aggregate results across all five quintiles (p-value = 0.394), indicating that herding in large shares cannot be explained by benchmark herding when the index (benchmark) is proxied by the FTSE/JSE Top 40 Index. Yet, it is also possible that unit trusts follow each other into other indices not controlled in this dissertation, particularly those which make up the benchmark performance indicator of each respective fund<sup>34</sup>.

In sum, the results provided in Table 7 suggest that unit trusts follow other unit trusts in large shares and follow their own trades in small shares. After controlling for “blue-chip” benchmark herding, the former could indicate that unit trusts herd because of reputational or cost trade-offs.

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<sup>34</sup> Refer to chapter 6: Areas for further research.

## Chapter 5: Conclusion

Various theories have been proposed for the drivers of herding behaviour, while the empirical results of previous studies (e.g., Wermers 1999; Sias 2004; Choi and Sias 2009; and Brown et al., 2014) largely supports the investigative herding, style investing, and informational cascades explanations. More recent work (e.g., Holmes et al., 2013; Gavriilidis et al., 2013; Popescu & Xu, 2014; and Popescu & Xu, 2018) has also contributed to the reputational herding hypothesis.

This dissertation contributes to the empirical literature on herding by investigating the South African equity unit trust industry. Employing the Sias measure of herding to the sample of 148 general equity unit trusts over the period from December 2012 to March 2020, this dissertation finds an overall level of herding (defined as the cross-sectional correlation between investors' demand for a given share in consecutive quarters) of 13.73% (significant at the 1% level), which is in between other comparable emerging market studies, and supports the alternative hypothesis that unit trusts herd in shares. Moreover, the average contribution of cross-correlation arising from unit trusts following the lag share-demand of other unit trusts is 38%, (significant at the 1% level) which suggests that herding could be driven, at least in part, by intent.

By analysing the interaction of herding behaviour under different market states, namely market returns and volatility, this dissertation demonstrates, consistent with recent empirical work (e.g. Holmes et al., 2013; and Kempf et al., 2009) and the hypotheses that unit trust herding is driven, at least in part, by reputational and/or informational payoffs, after controlling for net fund flows, momentum, and share-size style trading strategies. Particularly, this dissertation found that aggregate herding was 19% more prevalent in down markets than in up markets, 36% more in low relative to high market return states, 12% more prevalent in volatile markets than in tranquil markets, and 30% more in increasing relative to decreasing market volatility states. However, the differences between market states are not significant at the 5% level, indicating that herding does not interact with the level or direction of market returns and volatility.

Furthermore, this dissertation found strong evidence that unit trusts tend to follow other unit trusts in large shares and follow their own lag trades in smaller capitalization shares. After controlling for "blue-chip" benchmark herding, the former could indicate that unit trusts herd as a result of reputational or cost trade-offs.

In sum, the results provide strong evidence of unit trust herding across the general equity market, but this is not conclusively predicated by intent. The evidence indicates that unit trusts could herd intentionally (e.g., due to reputational/cost trade-offs, or the incentives for poor-quality fund managers to follow the actions of superior quality fund managers) or due to other reasons (e.g. fund mandate or industry benchmark herding).

The results of this dissertation are interesting due to the focus on South African unit trusts which has received relatively little attention in the scope of herding, particularly motivated by intent. South Africa has a well-functioning stock market with extensive regulation, contributing to greater information transparency, which further supports the robustness of the results of an intentional herding study of this nature. Furthermore, the results of this dissertation may be useful to existing and prospective investors (principals) in equity unit trusts as it provides evidence that fund managers' (agents') decisions are not always supported by fundamental or rational motives. Moreover, this dissertation demonstrated that the relative peer assessment of unit trust performance is not straightforward given the apparent tendency of fund managers to intentionally follow the trades (and, hence, performance) of their fellow managers. One must, therefore, carefully consider the returns performance in context of other factors, including environmental (market) signals that may influence fund managers to herd intentionally.

## Chapter 6: Areas for further research

In this section this paper provides areas for further research that has not been previously examined in the scope of herding behaviour within South Africa.

— *Is reputational herding more prevalent in certain institutions?*

Sias (2004) proposed a method of deriving the contributions of reputational herding: institutional investors should be more likely to follow similarly classified institutions than differently classified institutions if reputational concerns indeed drive herding behaviour. The propensity of each institutional investor type (e.g., banks, insurance companies, unit trusts, independent advisors, and pension funds) to engage in herding is tested using average same and different investor-type contribution measures (Choi & Sias, 2009). Although Choi & Sias (2009) find mixed support for the reputational herding hypothesis, the same tests can be applied in the South African unit trust industry given that unit trusts are most likely to experience investor flows as a result of changes in their reputation (Dasgupta et al., 2011). Further, Choi & Sias (2009) found no evidence that U.S. unit trusts and independent advisors (whom, theoretically, should be most concerned with their reputation) engage in reputational herding. One could investigate if such results are consistent on the JSE Limited (which is underdeveloped by USA standards and therefore subject to relatively less transparent information flows). The author of this dissertation recognises, however, that a reputational herding study requires a more substantial dataset with all types of institutional investors on the JSE Limited. Therefore, one would need extend the sample size to evaluate whether different investor types follow similarly classified counterparts.

— *Does fund size or performance impact the level of intentional herding?*

Within a relatively small (undeveloped) market as South Africa, it is possible that herding results from smaller, less-prestigious, or poor performing institutions (fund managers) following the trades of other more established, better-performing institutions. For example, Popescu & Xu (2018) examined unit trust herding conditioned on fund performance and found that poorly performing funds herd more than well-performing funds and was more so pronounced in bear markets than in bull markets. In this dissertation it was deduced that reputational/career concerns and also partly informational payoffs could drive such behaviour.

This question can be investigated by excluding top-tier (large size) or stronger performing funds from the population and examining the differences in herding measure to that of the original study, similar to the approach conducted by Holmes et al. (2013). Another method proposed by Popescu & Xu (2018) is to partition the unit trust herding measure into winning and losing funds independently, with winning (losing) funds defined based on their raw lagged fund returns.

— *Is industry herding merely a result of style investing models (e.g., size and book-to-market styles)?*

The Barberis & Shleifer (2013) style model requires that style herding behaviour exist and that this herding impacts prices. This dissertation did not incorporate fund returns data and therefore scoped out investigations into the price impact of herding behaviour. If price data is incorporated into the study, one could also investigate the destabilizing effect of unit trust herding on the JSE limited.

— *Segregation of herding measure: focus on sector.*

Gavriilidis et al. (2013) filtered their herding results for sectors within the general equity market. Their argument was the intentional herding could be exhibited based on market as well as sector states (e.g., returns, volatility, and trade volume). A similar methodology could be applied within the South African equity market to examine the propensity for sector funds to drive overall share herding behaviour.

— *Indexing – is herding merely a manifestation of passive investment strategies?*

This dissertation examined herding in active trades. Unit trust herding could also merely be as a result of passive investment strategies or benchmark herding: i.e., there could be evidence of herding merely because a number of funds are following index tracker portfolios. From Table 1 and Table 7, one can observe that the market capitalization of JSE limited is dominated by large-cap shares. As such, index tracking, particularly within the major blue-chip indices (such

as the FTSE/JSE Top 40 Index), could be driving unit trust herding within the general equity market as a whole.<sup>35</sup>

The implications are that if unit trusts are merely following index trackers, then it could be argued that there are few (if any) true active managers left in South Africa. In that case, one could determine if there is any value provided by fund managers to justify the fees. One could compare the returns on index trackers to unit trust industry returns: if the unit trust returns are less, perhaps the herding phenomenon is evidence that unit trusts are engaging in mutually destructive behaviour.

— *Is industry herding merely a result of fund style investing models (value and growth funds)?*

The unit trust industry population can be split into two categories based on fund style classification: value funds and growth funds. By investigating the trading patterns and investment philosophies of these separate categories, one could deduce which funds would be prone to engage in herding behaviour, whether it be intentional ('true') or unintentional ('spurious') herding. From this, one could then compare the empirical evidence from the accumulated funds data to the initial hypothesis to conclude on the tendency of a specific fund style manager to engage in such behaviour.

— *Does information uncertainty drive share-herding – examination with analyst recommendations.*

Sias (2004) and Chan et al. (2005) provide evidence suggesting that institutional investors herd into and out of shares with high levels of information uncertainty – i.e., higher informational ambiguity may prompt institutional investors to engage in herding behaviour as a means of resolving this ambiguity. Information uncertainty in shares originates, in part, from disparate analyst earnings forecasts or trade recommendations (Brown et al., 2014). One can then gauge the interaction between share herding behaviour and information uncertainty, approximated by the dispersion of analysts' earnings forecasts or trade recommendations. Brown et al. (2014)

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<sup>35</sup> As mentioned previously, this dissertation controlled for "benchmark herding" by removing index-tracker classified funds from the dataset; although, there could still be a bias in the results as fund managers may have an inherent preference for constituent shares of "blue-chip" indices (for example, due to the benchmark against which the fund performance is being assessed), while other institutions may face fund mandate or other regulatory constraints which require them to weight their portfolio towards larger capitalization shares.

found that unit trust herds tend to move in the same direction as analyst recommendation changes (upgrade/downgrade), and specifically that larger institutional investors (considered to be more sophisticated) are more sensitive (i.e., react more intensely) to analyst recommendation downgrades than to upgrades. This suggests that investors (particularly larger institutions) are aware of analyst biases (conflicts of interest) and are, thus, more sceptical with share upgrade recommendations (Brown et al., 2014).

— *Examining the window dressing phenomenon.*

The ‘window dressing’ explanation for intentional herding is premised on the convergence of trading activity around the time of release of performance data. In the case of professional fund managers in South Africa, fund reports are released on a quarterly basis which allows other fund managers (and its customers) to view and compare the fund holdings and performance metrics at least every 3 months. If the ‘window dressing’ explanation holds true, one would expect the intensity of herding measure to increase at quarter-ends (relative to month-end) when fund managers imitate the trades of others in anticipation of the release of quarterly holdings and performance data. Conversely, one would expect to see no significant differences in herding measure intensity across months when herding results solely from spurious motives such as relative homogeneity or characteristic herding.

Similar to the approach taken by Holmes et al. (2013), one can partition the sample of observations into monthly herding measures and compare the results from the first, second and third month of each quarter to draw insights into the sources of herding behaviour. Although, monthly holdings snapshot data could not be publicly available, as was the case at the time of writing this paper, which could provide a practical limitation on this type of analysis.

## Appendix: FTSE/JSE All-Share Index – market price

Quarter-end	Price (ZAR)	Log-returns	Log-returns (H-M-L)	Returns direction (UP-DOWN)	Quarterly Std. dev (DAILY prices)	Std. dev (H-M-L)	Change in Std. dev (INC/DEC)
6/29/12	33,708	-	-	-	0.87%	MID	INCREASING
9/28/12	35,758	5.90%	HIGH	-	0.72%	LOW	DECREASING
12/31/12	39,250	9.32%	HIGH	UP	0.55%	LOW	DECREASING
3/28/13	39,861	1.54%	MID	DOWN	0.62%	LOW	INCREASING
6/28/13	39,578	-0.71%	MID	DOWN	1.25%	HIGH	INCREASING
9/30/13	44,032	10.66%	HIGH	UP	0.92%	MID	DECREASING
12/31/13	46,256	4.93%	HIGH	DOWN	0.82%	MID	DECREASING
3/31/14	47,771	3.22%	MID	DOWN	0.71%	LOW	DECREASING
6/30/14	50,945	6.43%	HIGH	UP	0.51%	LOW	DECREASING
9/30/14	49,336	-3.21%	LOW	DOWN	0.63%	LOW	INCREASING
12/31/14	49,771	0.88%	MID	UP	1.21%	HIGH	INCREASING
3/31/15	52,182	4.73%	HIGH	UP	0.95%	MID	DECREASING
6/30/15	51,807	-0.72%	LOW	DOWN	0.70%	LOW	DECREASING
9/30/15	50,089	-3.37%	LOW	DOWN	1.42%	HIGH	INCREASING
12/31/15	50,694	1.20%	MID	UP	1.05%	HIGH	DECREASING
3/31/16	52,250	3.02%	MID	UP	1.37%	HIGH	INCREASING
6/30/16	52,218	-0.06%	MID	DOWN	1.09%	HIGH	DECREASING
9/30/16	51,950	-0.51%	MID	DOWN	0.84%	MID	DECREASING
12/30/16	50,654	-2.53%	LOW	DOWN	0.94%	MID	INCREASING
3/31/17	52,056	2.73%	MID	UP	0.72%	LOW	DECREASING
6/30/17	51,611	-0.86%	LOW	DOWN	0.64%	LOW	DECREASING
9/29/17	55,580	7.41%	HIGH	UP	0.62%	LOW	DECREASING
12/29/17	59,505	6.82%	HIGH	DOWN	0.59%	LOW	DECREASING
3/29/18	55,475	-7.01%	LOW	DOWN	1.04%	HIGH	INCREASING
6/29/18	57,611	3.78%	HIGH	UP	1.01%	HIGH	DECREASING
9/28/18	55,708	-3.36%	LOW	DOWN	0.98%	MID	DECREASING
12/31/18	52,737	-5.48%	LOW	DOWN	1.29%	HIGH	INCREASING
3/29/19	56,463	6.83%	HIGH	UP	0.81%	MID	DECREASING
6/28/19	58,204	3.04%	MID	DOWN	0.79%	MID	DECREASING
9/30/19	54,825	-5.98%	LOW	DOWN	0.86%	MID	INCREASING
12/31/19	57,084	4.04%	HIGH	UP	0.76%	MID	DECREASING
3/31/20	44,490	-24.93%	LOW	DOWN	2.96%	HIGH	INCREASING

Source: Investing.com (2020)

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