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DYNAMIC HERDING ANALYSIS IN A FRONTIER MARKET

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ABSTRACT

We use constant coefficient and time-varying parameter approaches to examine herding in the context of a frontier market. Our sample comprises of all companies listed on the Trinidad and Tobago Stock Exchange from January 2001 to December 2014. We find significant evidence of herding across the market, which is more prominent for smaller stocks. Microstructures, including liquidity and volatility, intensify herd behavior, except for larger firms. Additional analyses show that herding is present in both up and down markets, but is stronger during rising markets. The time-varying analysis, based on a state-space Kalman filter, further establishes that herding, though quite prevalent, is not a static feature of the market but evolves throughout the sample period. Specifically, it oscillates between greater herding to anti-herd behavior, as investors identify themselves with crises and better information access respectively.

JEL Classification: G02, G12, G14, G15.

Keywords: Herding, Frontier Markets, Market Microstructures, Time-Varying Herding, Kalman Filter

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ABSTRACT

We use constant coefficient and time-varying parameter approaches to examine herding in the context of a frontier market. Our sample comprises of all companies listed on the Trinidad and Tobago Stock Exchange from January 2001 to December 2014. We find significant evidence of herding across the market, which is more prominent for smaller stocks. Microstructures, including liquidity and volatility, intensify herd behavior, except for larger firms. Additional analyses show that herding is present in both up and down markets, but is stronger during rising markets. The time-varying analysis, based on a state-space Kalman filter, further establishes that herding, though quite prevalent, is not a static feature of the market but evolves throughout the sample period. Specifically, it oscillates between greater herding to anti-herd behavior, as investors identify themselves with crises and better information access respectively.

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1. Introduction

Herding alludes to investors imitating other investors' actions whilst ignoring their own information set when it differs from what everyone else is doing (Banerjee, 1992; Bikhchandani *et al*., 1992). This type of investor behavior stands at crossroads with Samuelson and Fama's Efficient Market Hypothesis (EMH)[1], which not only initiated tremendous debate, modeling and commentary but also remained a prominent financial theory from the 1960s till the turn of century, when financial economists and statisticians began to realize that psychology, human biases and preferences had a role to play in how prices and markets behaved.

Behavioral finance emerged as a potent critique of the EMH. Rationality, as a prime characteristic of utility-maximizing investors, began to be revisited. The academic attention, which was focused on randomness and unpredictability of stock prices, magnified to include the possibility that stock prices may be partially predictable. Cognitive psychology, with its biases and irrationality, began to be considered as one of the reasons that explain human decision making, especially under stress and uncertainty. Herding was one of them.[2]

Whether herding occurs due to rational motivations (Calvo and Mendoza, 2000); reputational and conformist preferences, (Scharfstein and Stein, 1990; Bikhchandani and Sharma, 2001), peer pressure and positive-feedback strategy (Lakonishok *et al.*, 1992), or cognitive biases

[1] Sameulson (1965), Fama (1963; 1965a; 1965b; 1970)

[2] Banerjee (1992) defines herding as "everyone doing what everyone is doing, even when their private information suggest doing something quite different." and notes that when investors act on the information of others, it creates a situation whereby their own private information which they have ignored becomes less informative to others. This reduction in informativeness could at times be of more harm to society than beneficial.

(Lux, 1995; Devenow and Welch, 1996), it has garnered significant academic recognition and reflection. Herding could also be intentional (Devenow and Welch 1996, Clement and Tse 2005) or spurious (Bikhchandani and Sharma 2001, Wermers 1999).

While herding can lead to idiosyncratic, short–lived fluctuations, leading to excess volatility (due to possible asset mispricing that results from a lack of attention to economic fundamentals) and systemic risk (Bikhchandani *et al.* 1992), it can also lead to sub-optimal diversification because if everyone executes similar trades, locating and investing in negatively correlated securities can be difficult, a chore which many international portfolio investors in frontier markets seem to be enthusiastic about lately.

A growing body of literature on herding behavior focuses on emerging markets (for example Chang *et al.*, 2000; Chiang *et al.*, 2010; Bhaduri and Mahapatra, 2013; Xie *et al.*, 2015). In recent years, however, frontier markets have captured the attention of international portfolio investors, as they search for greater diversification benefits with the underlying desire of benefitting from their limited integration with international markets (De Groot *et al.* 2012). Further, frontier markets appear to be ideal candidates for herding behavior due their unique characteristics – they are in the initial phases of financial development, with small market capitalizations and trade volumes, misinformation or bottlenecks in information flows, limited investment culture and expertise and various institutional designs, or dearth thereof. These unique features, coupled with the fact that very few studies in the literature address herding behavior in frontier markets (Guney *et al.* 2016, Balcilar *et al.* 2013, Erdenetsogt *et al.* 2016)[3]

[3] A sizeable body of research on herding behavior exists for developed and more prominent emerging markets (As an illustration, Chang and Khorana (2000) studied different international markets, in the United States, Hong Kong, Japan, South Korea and Taiwan and Almeida *et al.* (2012) tested whether herding behavior was present in Latin American stock markets.

motivate our present study. Specifically, we examine a frontier market – the Trinidad and Tobago Stock Exchange (TTSE) for possible herding behavior, its time-varying nature and the effect of market microstructures on herding. There are currently 32 companies listed on the Trinidad and Tobago Stock Exchange (TTSE). Given the small number of securities being traded on this exchange, it can be argued that the TTSE lacks desired breadth and depth. Such a market can be prone to considerable price volatility, where small movements in any market segment can generate substantial and potentially damaging market-wide price movements. These features provide an ideal setting for possible herd behavior.

Therein lies our principal contribution. We assess herding from the perspective of a frontier market using two approaches – a constant coefficient approach and a time-varying approach. As far as we are aware, there is no published work that considers the evolution of herding behavior in a frontier market setting.

While we aim to study the nature of herding estimates in the TTSE, we are mindful that volatility, liquidity and asymmetric market states may have an impact on herding behavior and that omission of these variables can lead to incomplete deductions (Chen *et al*, 2013; Chordia *et al*., 2008; Tian *et al.*, 2015). We therefore introduce these variables in our empirical analysis, to ascertain their effects on herding in the framework frontier market.

From the stance of a frontier market therefore, our contribution to literature is three-fold, as we: 1) provide information on its herding behavior; 2) Undertake a time-varying analysis of herding behavior in such a market, and 3) explore the effects of its market microstructure on herding.

We organize the remainder of this paper as follows: Section 2 outlines the methodology and section 3 presents the data and descriptive statistics. The empirical evidence on herding is presented in Section 4, while section 5 concludes.

2. Methodology

The initial step in our methodology to assess herding involves estimating the return dispersion. For this purpose, we apply the Cross Sectional Absolute Deviation (CSAD) of returns, proposed by Chang *et al.* (2000). This model is a variant of Christie and Huang (1995) methodology, which uses Cross Sectional Standard Deviation of Returns (*CSSD*) to detect herding behavior.

The *CSAD* is defined as

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

Chang *et al.* (2000) model is based on the assumption that herding behavior is more pronounced during periods of relatively large price swings and could be detected by observing the dispersion of the cross sectional stock returns. $CSAD_t$ is the measure of stock return dispersion, N is the number of stocks (firms) in the market or portfolio, and $R_{i,t}$ and $R_{M,t}$ are the values of a firm's realized return and equally weighted realized return of firms on day t.

This model is derived from the Capital Asset Pricing Model (CAPM). The zero-beta CAPM states that

$$E(R_{i,t}) = R_{\beta 0} + \beta_i E(R_{m,t} - R_{\beta 0})$$

where; $R_{i,t}$ is the return of stock i at time t, $R_{m,t}$ is the market portfolio's return at time t, $R_{\beta 0}$ is the return on the zero-beta portfolio and β_i is stock i's systematic risk. E is the expectations operator.

We can write the absolute value of deviation of stock i's expected return from market return as:

$$\left|E(R_{i,t}) - R_{m,t}\right| = \left|R_{\beta 0} + \beta_i E(R_{m,t} - R_{\beta 0}) - R_{m,t}\right|$$

It follows that:

$$\left|E(R_{i,t}) - R_{m,t}\right| = \left|(R_{\beta 0} - R_{m,t}) + \beta_i \left[E(R_{m,t}) - R_{\beta 0}\right]\right|$$
$$\left|E(R_{i,t}) - R_{m,t}\right| = \left|\left[E(R_{m,t}) - R_{\beta 0}\right][\beta_i - 1]\right|$$

For N number of stocks, we can define the mean cross-sectional absolute value of deviation (MAD) as follows:

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

If we assume that realized returns are a good proxy for expected returns, we return to Eq. (1) for $CSAD$. Substituting the definition of $\left|E(R_{i,t}) - R_{m,t}\right|$ from earlier;

$$MAD_t = \frac{1}{N}\left|\left[E(R_{m,t}) - R_{\beta 0}\right][\beta_i - 1]\right|$$

Since $\frac{\partial MAD_t}{\partial \left|E(R_{m,t})\right|} = \frac{1}{N}\sum_{i=1}^{N}\left|\beta_i - 1\right| > 0$ and $\frac{\partial^2 MAD_t}{\partial \left|E(R_{m,t})\right|^2} = 0$, we infer that *MAD* is a positive and linear function of absolute market return. What follows is that any non-linear relationship must be an outcome of some market dissonance including, but not limited to, irrational investor behavior where a herd disregards its beliefs in favor of the market sentiment.

Chang *et al.* (2000) argue that when herding occurs, where market participants ignore their own priors and imitate the behavior of other market participants, it causes periods whereby the market prices fluctuate significantly. As mentioned earlier, during these periods, the relationship depicted by CAPM between market return and return dispersion will no longer be valid. Instead the relationship could increase or even decrease in a nonlinear fashion.

Alternatively, Christie and Huang's (1995) formulation uses CSSD to measure dispersion and states that herding behavior is more apparent in periods when the market is under extreme stress. CSSD is expressed as:

$$CSSD_t = \sqrt{\frac{\sum_{i=0}^{N}\left(R_{i,t} - R_{m,t}\right)^2}{N-1}} \tag{2}$$

Where, *N* is the number of firms in the portfolio, $R_{i,t}$ is the observed return of stock *i* at time *t* and $R_{m,t}$ is the cross sectional average inventory of *N* returns in the portfolio at time *t*. However, the $CSSD_t$ can be sensitive to outliers, as it is calculated by squared return deviations. We therefore do not adopt this measure, as outliers are a common feature of frontier equity market data.

For detecting herding activity within the TTSE, a generalized form of the Chang *et al*. (2000) formulation is used which is consistent with previous studies (Balcilar *et al*., 2013; Yao *et al.,* 2014).

$$CSAD_t = \varphi_0 + \varphi_1 \left| R_{m,t} \right| + \varphi_2 R_m^2 + \varepsilon_t \qquad (3)$$

This model aims to detect any significant clustering in the dispersion of returns during periods of extreme price fluctuations or movement in the market. A statistically significant negative coefficient of φ_2 indicates that herding is evident, as during periods of market stress a decline in return dispersion is expected.

Although this definition of absolute deviations has been praised for its sound theoretical foundation, there are several inherent limitations. First, in Eq. (3) the two explanatory variables $R_{m,t}$ and $(R_{m,t})^2$ could potentially exhibit a high level of multicollinearity. To overcome this problem, we follow Xie *et al.* (2015), and modify the second term Eq. (3) by de-meaning the market return.

$$CSAD_t = \varphi_0 + \varphi_1 \left| R_{m,t} \right| + \varphi_2 \left(R_{m,t} - \overline{R}_{m,t} \right)^2 + \varepsilon_t \qquad (4)$$

where $\overline{R}_{m,t}$ is the arithmetic mean of $R_{m,t}$. This adjustment should overcome any multicollinearity issues and produce more reliable standard errors.

Second, with the use of high frequency time series market data, it is expected that there would be a high level of serial correlation. In order to address this issue, we use Newey and West (1987) "heteroscedasticity and autocorrelation consistent standard errors" to calculate the coefficients for the estimated regression. We also control for the lagged dependent variable

($CSAD_{t\text{-}1}$) to ensure that our results are not a spurious restatement of potential autocorrelation in the dependent variable:

$$CSAD_t = \varphi_0 + \varphi_1 \left| R_{m,t} \right| + \varphi_2 \left(R_{m,t} - \overline{R}_{m,t} \right)^2 + \varphi_3 CSAD_{t-1} + \varepsilon_t \tag{5}$$

Third, this model is based on a static specification whereby the parameters of the model are assumed to remain the same over time. This means that the model fails to consider the fact that herding may be a dynamic feature of the market and changes with investor behavior and market characteristics. The static model also ignores the occurrence of structural breaks and regime changes. This can create varying states of uncertainty in a regime-changing environment, which is likely to impact herding. Studies have also shown that herding is more pronounced during periods of extreme market stress (Chiang *et al*. 2007 and Boyer *et al.* 2006). It is therefore important to assess herding from a time-varying perspective, thereby identifying the periods when herding was indeed present and the extent of this herding.

To capture the evolving nature of herding in the TTSE, a state-space model combined with the Kalman-filter is adopted. It is expected that herding in this market would be time varying, since this market is in its embryonic stages of development and has undergone several institutional changes over the sample period. The Kalman-filter based model can be expressed as:

$$CSAD_t = \varphi_0 + \varphi_1 \left| R_{m,t} \right| + \varphi_2 \left(R_{m,t} - \overline{R}_{m,t} \right)^2 + \varphi_3 CSAD_{t-1} + \varepsilon_t \tag{6}$$

$$\varphi_{i,t} = \varphi_{i,t-1} + \nu_{i,t}, \nu_{i,t} \sim N\left(0, \sigma^2\right) \quad \text{where } \ i = 0,1,2 \text{ and } 3 \tag{7}$$

Eq. (6) is a measurement equation and $\left[\varphi_{0,t}, \varphi_{1,t}, \varphi_{2,t}, \varphi_{3,t}\right]$ is a vector of state variables. Eq. (7) is a transition equation and the state variables are assumed to evolve with a random walk process. Eq. (6) and (7) can then be represented in a state space form. The Kalman-filter estimation in conjunction with the state space methodology provides a favorable tool to work with variables that cannot be observed, including $\varphi_{0,t}, \varphi_{1,t}, \varphi_{2,t}, \varphi_{3,t}$. The use of state space modeling has gained prominence over the years especially in macroeconomics and finance; and has been used in a number of studies (for example Harvey 1989; Shumway and Stoffer 2000; Chiang *et al.* 2013).

State space models differentiate between a measurement equation and a transition equation. The measurement equation expresses the observed variables in terms of unobserved state variables. The transition equation depicts the evolution of the unobserved state variables over time. The innovations in the measurement and transition equations are both independent and identically distributed random variables. Estimation of the parameters in Eq. (6) and (7) is achieved using Berndt *et al*. (1974) algorithm, that is, by maximizing the Likelihood function. The Kalman filter is used to produce smooth estimates of the state variables $\varphi_{0,t}, \varphi_{1,t}, \varphi_{2,t}, \varphi_{3,t}$.

3. Data and Descriptive Statistics

The data applied in this study are obtained from the TTSE. They comprise of daily returns for each common stock listed on the TTSE, over the period January 2001 through December 2014. We chose this sample size as we deem it sufficiently long to capture a true picture of herd behavior on the TTSE and how it evolves over time. The sample consists of 32 stocks, and the returns for each stock are computed as $R_t = 100 \times \left[\log(P_t) - \log(P_{t-1})\right]$ where P_t denotes the closing daily stock price. R_m is computed as the equally weighted average of the daily returns of the 32 listed stocks.

Apart from considering herding at the overall market level, we also study herding through four portfolios ranked according to size (market capitalization). Since herding varies with information flows, it would be interesting to determine whether there are indeed differences in herding behavior between large and small capitalization portfolios. We anticipate that there should be more herding in small capitalization stocks; as such stocks are associated with lower information flows and increased information asymmetry.

We create four size-based portfolios as follows. For each year of the sample period, all firms are ranked according to their market capitalization as of December of the previous year, and then divided into four equal groups. Once portfolios are formed in this manner, their composition is kept unchanged for the remainder of the year. The $CSAD_t$ is computed separately for each quartile in keeping with Eq. (1), where $R_{i,t}$ denotes the daily returns of the individual stocks (i) in the respective quartile and $R_{m,t}$ is an equally weighted average of the daily returns of each stock in the quartile.

Table 1 contains summary descriptive statistics of $R_{m,t}$ and $CSAD_t$ for the overall TTSE and the four size-based portfolios. Quartile 4 is the largest size portfolio while Quartile 1 is the smallest. Overall, the mean returns for the market and each portfolio are positive, suggesting that on average, the TTSE performed positively over the sample period. Quartile 4 has the highest mean returns, while Quartile 1 has the smallest, which may be attributed to the relative sizes of these portfolios. The most volatile portfolio appears to be Quartile 2, as it has the highest standard deviation, while Quartile 3 has the lowest and may therefore be regarded as the least volatile. This might suggest that Quartile 2 has the highest level of uncertainty among the portfolios. Turning to the *CSAD* values, its highest average is observed for the Quartile 1, and is most volatile for Quartile 4. We also report the Augmented Dickey Fuller (ADF) test statistics, which convincingly reject the null hypothesis of a unit root (non-stationarity) in $R_{m,t}$ and *CSAD* for each quartile and the TTSE.

Table 1

Descriptive Statistics for overall market and each size based portfolio

Table 1 reports the mean and standard deviation of returns (R_M) and cross-sectional standard deviation (*CSAD*) for the overall TTSE and each size based portfolio, for the sample period January 2001 to December 2014. The Jarque-Bera normality test, Augmented Dickey (ADF) test for stationarity and Ljung-Box (LB) portmanteau serial correlation tests for 10 lags are also reported. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

	Variable	Mean	Std. Dev.	Jarque-Bera	ADF	LB *Q*-Stat
TTSE	$R_{m,t}$	0.0246	0.6254	8931196***	-15.3507***	92.04***
	CSAD	0.4021	1.1091	8805392***	-11.5570***	519.68***
Quartile 4 (Largest)	$R_{m,t}$	0.0514	0.9206	207361***	-23.3353***	80.434***
	CSAD	0.4216	1.4943	11687310***	-7.4243***	290.53***
Quartile 3	$R_{m,t}$	0.0384	0.3604	989897***	-13.8114***	229.93***
	CSAD	0.3308	0.8361	107000000***	-13.2638***	580.07***
Quartile 2	$R_{m,t}$	0.0359	1.1120	86867853***	-37.6018***	62.309***
	CSAD	0.3476	1.1172	20939435***	-14.6740***	446.61***
Quartile 1 (Smallest)	$R_{m,t}$	0.0204	0.5951	41951343***	-27.4266***	293.02***
	CSAD	0.4328	1.3447	38027265***	-13.6878***	502.07***

To gain more insights into the dynamics of the data, we test for the presence of serial correlation in R_M and *CSAD* for the TTSE and each size quartile. For this, we apply the Ljung-Box (LB) portmanteau test of autocorrelation for 10 lags. All of the *Q*-statistics for this test are statistically significant at the 1% level, denoting the presence of serial correlation. This suggests inefficiencies in the return-generating process in the TTSE, which is expected for a frontier market, as it is in nascent developmental stages and is informationally inefficient (see Arjoon, 2016; Arjoon *et al.* 2016). The presence of serial correlation justifies the inclusion of the lagged dependent variable in our regression Eq. (5) to control for serial correlation.

4. Empirical results and discussion

4.1. Estimates of herding behavior

Table 2 provides the estimates for the static return dispersion model described in Eq. (5). The model is estimated using the Newey-West (1987) heteroscedastic and autocorrelation consistent estimator. As indicated earlier, a negative value on the coefficient of $\left(R_{m,t} - \overline{R}_{m,t}\right)^2$ is consistent with herding behavior. In line with our expectations, the results in Panel A clearly suggest that herding exists in the overall market, as the herding coefficient in column (2) is negative and statistically significant at the 1% level.[4] This result corroborates our expectations – many investors base their trading decisions on those of their peers, leading to significant herding behavior.

[4] Our result is robust to the auto-correlative nature of the dependent variable, as we include a lag of the dependent variable $CSAD_{t-1}$ in the model specification.[4] This result contrasts those of Yao *et al.* (2014) – when the lagged dependent variable is included in their herding model, the herding coefficient is no longer statistically significant for Chinese A-Share markets, suggesting that previous evidence of herding which they uncovered was a restatement of serial correlation. The adjusted R^2 of 0.967 indicates that the estimated equation has high explanatory power, which also justifies the inclusion of the lagged dependent variable in the specification.

Table 2

Regression estimates of herding behavior on the TTSE (overall market and sized based portfolios).

Table 2 presents the estimated coefficients of Eq. (5): $CSAD_t = \varphi_0 + \varphi_1 \left|R_{m,t}\right| + \varphi_2 \left(R_{m,t} - \overline{R}_{m,t}\right)^2 + \varphi_3 CSAD_{t-1} + \varepsilon_t$ Panels A and B report the regression estimates for the overall market and size based quartile portfolios respectively. Each quartile in Panel B is constructed based on the closing annual market capitalization of the individual stocks listed on the TTSE. The quartiles are re-weighted each year, based on changes in the market capitalization of individual stocks listed in the market. Portfolio 4 is the largest size based quartile, while portfolio 1 is the smallest. $CSAD_t$ is the cross sectional absolute standard deviation (measure of return dispersion) and R_m is the equally weighted realized return of all (1) firms listed on the TTSE and (2) firms in each quartile. $\overline{R}_{m,t}$ is the arithmetic mean of $R_{m,t}$ and $CSAD_{t-1}$ is the 1-day lag variable of $CSAD_t$. The numbers in parenthesis are *p*-values. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	$\left\|R_{m,t}\right\|$	$\left(R_{m,t} - \overline{R}_{m,t}\right)^2$	$CSAD_{t-1}$	Adj-R^2
Panel A: Market Portfolio				
TTSE	1.9201*** (0.003)	-0.0086*** (0.000)	0.0102*** (0.003)	0.9671
Panel B: Size Ranked Portfolios				
Quartile 4 (Largest)	1.6751*** (0.000)	-0.0282*** (0.000)	0.0422*** (0.001)	0.5829
Quartile 3	1.2950*** (0.000)	-0.0060** (0.010)	-0.0104* (0.073)	0.7860
Quartile 2	1.1826*** (0.000)	-0.0833*** (0.000)	-0.0226*** (0.0176)	0.7770
Quartile 1 (Smallest)	2.7473*** (0.000)	-0.0798*** (0.000)	0.0053 (0.674)	0.6724

The information environment in this market is asymmetric and opaque, where information on fundamentals is collected by few market participants. In the absence of such reliable market information available to the public, most investors, therefore, resort to herding. That is, they free-ride on their peers' information set. Some investors, who do possess reliable information on fundamentals, may instead base their trading decisions on those of other investors, and suppress their own private signals. This is because they may deem the information set or the information processing skills of their peers to be of superior quality. Such trading behavior will inhibit information on fundamentals from being brought to the market and therefore prices will be shaped by limited information, denoting an informationally inefficient market (see Arjoon, 2016). Our result corroborates prior analyses on herding in frontier markets, including Balcilar *et al.* (2013) for Gulf equity markets and Economou *et al.* (2016) for the Athens Stock Exchange, Erdenetsogt and Kallinterakis (2016) for the Mongolian Stock Exchange and Guney *et al*. (2016) for African stock markets.

Panel B reports the regression estimates for portfolio quartiles ranked according size (annual market capitalization). Such an analysis allows us to discern the differential effect of size on herding behavior. Indeed, prior research has shown that more information on fundamentals is collected and disseminated for larger stocks, relative to smaller stocks, as larger stocks receive more analyst coverage and display higher trading volume (McQueen *et al.* 1996; Chordia and Swaminathan, 2000). Moreover, sophisticated investors who make informed trading decisions such as institutional and international investors also tend to trade in large stocks (see Bae *et al.*, 2012).

We find that herding behavior is present across all size-based quartiles, as the estimated herding coefficients in column (2) are all negative and statistically significant. We also note that the magnitude of the herding coefficients become more negative as we move from quartile 3 to quartile 1, which is some indication that smaller stocks are associated with greater information asymmetry and herding behavior. It appears, however, that herding is stronger in quartile 4 relative to 3, despite more information on fundamentals being generated by analysts for firms in quartile 4. This may be attributed to the lack of investor expertise in accurately interpreting information produced by analysts. Many of them may not also fully understand equity valuation models and therefore cannot formulate private signals on equity pricing. To this end, it is more likely that their trading decisions for quartile 4 are based on the market trend and the actions of their peers, more so than quartile 3.

4.2. Herding and the market environment

Different states of the market environment can influence herd behavior, as it affects the beliefs, reactions to news and trading decisions of investors. We therefore assess how the market environment, in particular liquidity, volatility and the state of the market (up and down market conditions), influence herding on the TTSE.

4.2.1. *Liquidity and herding behavior*

Several studies have shown that liquidity has profound effects for the information environment in equity markets.[5] [6] One strand of these studies show that informational flows and efficiency improve with increased liquidity (for example Chordia *et al.* 2008; Tian *et al.*, 2015). On the contrary, other studies show liquidity to be associated with irrational investors and sentiment trading (see Baker and Wurgler, 2006; Deuskar *et al.* 2008; Brennan and Wang, 2007). Since liquidity is associated with information flows, it is particularly important to analyze its role in herding behavior.

To achieve this purpose, we include a liquidity interaction term in Eq. (5) as follows:

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[5] Key features of a liquid market include low transaction costs, market debt and breadth, swift order execution and order flow continuity (Sarr and Lybek, 2002).

[6] Other studies show that liquidity has implications for equity returns. For instance, earlier studies by Amihud and Mendelson (1986) and Datar et al. (1998) show that equity returns are positively related to market illiquidity. Pastor and Stambaugh (2003) find that the average return on stocks that are highly sensitive to liquidity exceeds that of stocks with a low sensitivity.

$$CSAD_t = \alpha + \varphi_1 \left| R_{m,t} \right| + \varphi_2 \left(R_{m,t} - \overline{R}_{m,t} \right)^2 + \varphi_3 Liq_t \text{ x } \left(R_{m,t} - \overline{R}_{m,t} \right)^2 + \varphi_4 Liq_t + \varphi_5 CSAD_{t-1} + \varepsilon_t \qquad (8)$$

Liq_t is the liquidity variable, measured by volume traded.[7] We use this measure of liquidity as it gauges the depth and breadth of the market, that is; numerous and large orders in volume that have a little impact on equity prices (see Sarr and Lybek, 2002). Statistically significant estimates of φ_3 would suggest that increase in liquidity has a significant impact on herding behavior on the TTSE.

[7] Several measures of liquidity are proposed in the literature, including the quoted and effective bid ask spread, order imbalances, volume traded, market turnover, the Amihud (2002) illiquidity measure, the price impact measure of Pastor and Stambaugh (2003) and the Amivest liquidity ratio. Each of these measures captures a different dimension of liquidity. For instance, volume traded, market turnover and the Amihud (2002) illiquidity measure capture market depth and breadth, order imbalances capture order flow and the bid-ask spread reflect transaction costs.

Table 3

Effects of liquidity on herding behavior.

This table presents the estimated coefficients of Eq. (8):

$$CSAD_t = \alpha + \varphi_1 \left| R_{m,t} \right| + \varphi_2 \left(R_{m,t} - \overline{R}_{m,t} \right)^2 + \varphi_3 Liq_t \times \left(R_{m,t} - \overline{R}_{m,t} \right)^2 + \varphi_4 Liq_t + \varphi_5 CSAD_{t-1} + \varepsilon_t$$

Panels A and B report the effects of liquidity of herding behavior on the overall market and size based quartile portfolios respectively. Each quartile in Panel B is constructed based on the closing annual market capitalization of the individual stocks listed on the TTSE. The quartiles are re-weighted each year, based on changes in the market capitalization of individual stocks listed in the market. Portfolio 4 is the largest size based quartile, while portfolio 1 is the smallest. $CSAD_t$ is the cross sectional absolute standard deviation (measure of return dispersion) and R_m is the equally weighted realized return of: (1) all firms listed on the TTSE and (2) firms in each quartile. $\overline{R}_{m,t}$ is the arithmetic mean of $R_{m,t}$ and $CSAD_{t-1}$ is the 1-day lag variable of $CASD_t$. $Liq_{m,t}$ is the liquidity variable and is measured by measured by daily volume traded and is computed as the ratio of daily volume traded to daily market capitalization. The numbers in parenthesis are *p*-values. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	$\left\|R_{m,t}\right\|$ (1)	$\left(R_{m,t} - \overline{R}_{m,t}\right)^2$ (2)	$Liq_t \times \left(R_{m,t} - \overline{R}_{m,t}\right)^2$ (3)	$CSAD_{t-1}$ (4)	Liq_t (5)	Adj-R^2 (6)
Panel A: Market Portfolio						
TTSE	1.9047*** (0.000)	-0.0114*** (0.000)	-4.81E-09** (0.024)	0.0147*** (0.001)	2.56E-11* (0.063)	0.9507
Panel B: Sized Ranked Portfolios						
Quartile 4 (Largest)	1.5230*** (0.000)	-0.0497*** (0.000)	1.36E-08*** (0.000)	0.0211** (0.048)	4.91E-09*** (0.001)	0.7228
Quartile 3	1.4494*** (0.000)	-0.0543*** (0.000)	-5.54E-08*** (0.000)	-0.0103 (0.149)	-2.10E-08*** (0.000)	0.8736
Quartile 2	1.7081*** (0.000)	-0.1013*** (0.000)	-9.06E-08*** (0.000)	-0.0053 (0.479)	-3.44E-08*** (0.000)	0.8601
Quartile 1 (Smallest)	2.2425*** (0.000)	-0.1478*** (0.000)	-1.91E-07*** (0.000)	0.2275*** (0.000)	-3.35E-08*** (0.000)	0.7526

Table 3 reports the regression results of Eq. (8) for the overall market and each of the size based quartiles. The results corroborate our findings of herding in Table 1, as the herding coefficients in column (2) are all negative and statistically significant at the 1% level. We further find that for the overall market and quartiles 3 to 1, φ_3 reported in column (3) is negative and statistically significant, suggesting that when liquidity rises, the negative association between the squared demeaned market return $\left(R_{m,t} - \bar{R}_{m,t}\right)^2$ and the return dispersion $CSAD_t$ intensifies. That is, when liquidity rises, there is an increased tendency for investors to herd with the market consensus. Such results may imply that higher liquidity, reflected by an increase in trading, is not related to the transmission of information on investors' private signals on fundamentals, but rather the decisions of other traders. Since this market is in its developing stages, much of the investors are not sophisticated. They may exhibit irrational behavior and trade on sentiments. Increased liquidity on the TTSE could suggest an increased presence of such investors, who are more likely to herd, which could also explain this result. We note that for quartile 4, however, φ_3 is positive and statistically significant, which means that higher liquidity of this portfolio attenuates herding. This result reflects an increase in the flow of information when trading increases in this portfolio, as investors who are less irrational base their trades on fundamentals instead of the decisions of their peers.

4.2.2. *Volatility and herding behavior*

Higher volatility is reflected in excessive price fluctuations that deviate from fundamentals. This produces increased market risk and uncertainty, causing investors to be unsure of how to react to news and events. Volatility therefore affects investors' beliefs and trading decisions.

To this end, we analyze how volatility affects herding behavior in the TTSE. We estimate the following regression, which includes a volatility interaction term:

$$CSAD_t = \alpha + \varphi_1 \left|R_{m,t}\right| + \varphi_2 \left(R_{m,t} - \bar{R}_{m,t}\right)^2 + \varphi_3 Vol_t \times \left(R_{m,t} - \bar{R}_{m,t}\right)^2 + \varphi_4 Vol_t + \varphi_5 CSAD_{t-1} + \varepsilon_t \qquad (9)$$

where volatility, given by Vol_t, is measured by the daily Generalized Autoregressive Conditional Heteroscedasticity (GARCH (1, 1)) variances. Statistically significant estimates of φ_3 would suggest that higher volatility has a significant impact on herding behavior.

Table 4 provides the estimates of regression Eq. (9). Again, our findings of herding in Table 1 are confirmed, as the herding coefficients in column (2) are all negative and statistically significant. For the overall market and quartiles 3 to 1, φ_3 given in column (3) is negative and statistically significant, indicating that higher volatility increases the incidence of herd behavior. This suggests that when risk and uncertainty rises, investors on the TTSE tend to base their trades on the beliefs and decisions of their counterparts, rather than gather information to trade on fundamentals (see Litimi *et al.* 2016). They may also abandon their private signals in favor of the trading decisions of their peers, as they may believe that the information set, beliefs or even investing knowledge and training of their peers are superior (see Venezia *et al*., 2011). Some of their peers may also have sustained profits in the past, and therefore investors may feel inclined to mimic the actions of these peers in times of increased uncertainty and risk. However, increased volatility appears to reduce herding in quartile 4, as φ_3 is positive and statistically significant. It is likely that investors in this quartile are more sophisticated, they accumulate and trade on information on fundamentals when uncertainty and risk increases, rather than relying on the beliefs of their counterparts.

Table 4

Effects of volatility on herding behavior

This table presents the estimated coefficients of Eq. (9):

$$CSAD_t = \alpha + \varphi_1 \left|R_{m,t}\right| + \varphi_2 \left(R_{m,t} - \bar{R}_{m,t}\right)^2 + \varphi_3 Vol_t \times \left(R_{m,t} - \bar{R}_{m,t}\right)^2 + \varphi_4 Vol_t + \varphi_5 CSAD_{t-1} + \varepsilon_t$$

Panels A and B report the effects of volatility on herding behavior for the overall market and size based quartile portfolios respectively. Each quartile in Panel B is constructed based on the closing annual market capitalization of the individual stocks listed on the TTSE. The quartiles are re-weighted each year, based on changes in the market capitalization of individual stocks listed in the market. Portfolio 4 is the largest size based quartile, while portfolio 1 is the smallest. $CSAD_t$ is the cross sectional absolute standard deviation (measure of return dispersion) and R_m is the equally weighted realized return of all (1) firms listed on the TTSE and (2) firms in each quartile. $\bar{R}_{m,t}$ is the arithmetic mean of $R_{m,t}$ and $CSAD_{t-1}$ is the 1-day lag variable of $CSAD_t$. Vol_t, is measured by the daily Generalized Autoregressive Conditional Heteroscedasticity (GARCH (1, 1)) variances. The numbers in parenthesis are *p*-values. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	$\left\|R_{m,t}\right\|$ (1)	$\left(R_{m,t} - \bar{R}_{m,t}\right)^2$ (2)	$Vol_t \times \left(R_{m,t} - \bar{R}_{m,t}\right)^2$ (3)	$CSAD_{t-1}$ (4)	Vol_t (5)	Adj-R^2 (6)
Panel A: Market Portfolio						
TTSE	1.8879***	-0.0076***	-0.0037***	0.0062***	-0.0015	0.9710
	(0.000)	(0.000)	(0.000)	(0.001)	(0.355)	
Panel B: Sized Ranked Portfolios						
Quartile 4 (Largest)	1.4398***	-0.0874***	0.0150***	0.0453***	0.0169***	0.6866
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	
Quartile 3	1.3480***	-0.0053**	-0.0029***	-0.0039	-0.0071**	0.7938
	(0.000)	(0.036)	(0.000)	(0.616)	(0.028)	
Quartile 2	1.1974***	-0.0866***	-0.0008*	-0.0150*	-0.0019	0.8601
	(0.000)	(0.000)	(0.055)	(0.069)	(0.724)	
Quartile 1 (Smallest)	2.7943***	-0.0595***	-0.0049***	0.0243**	-0.0309***	0.6795
	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)	

4.2.3. *Herding behavior under asymmetric market states*

A handful of studies have also recognized that herding can change when the market is rising or declining. Chang *et al*. (2000), Demirer *et al.* (2006) and Yao *et al.* (2014) find that herding is more pronounced during declining market conditions, as collectively, investors may be more inclined to engage in a "flight to safety" strategy during down markets. Qiao *et al* (2014) observe, however, that herding is more prominent during periods of rising markets. They attribute this pattern to investors acting on the advice of analysts who recommend buy orders more frequently than sell orders.

To test whether herding is asymmetric in rising as opposed to declining markets, we estimate the following equation:

$$\begin{aligned} CSAD_t = {} & \varphi_0 + \varphi_1 D \times \left|R_{m,t}\right| + \varphi_2 (1-D) \times \left|R_{m,t}\right| + \varphi_3 D \times \left(R_{m,t} - \bar{R}_{m,t}\right)^2 \\ & + \varphi_4 (1-D) \times \left(R_{m,t} - \bar{R}_{m,t}\right)^2 + \varphi_5 CSAD_{t-1} + \varepsilon_t \end{aligned} \tag{10}$$

D is a dummy variable that takes a value of 1 if $R_{m,t} < 0$ (declining market) and 0 otherwise (rising market).

Table 5 presents the estimated herding coefficients under declining (φ_3, given in column 3) and rising (φ_4, given in column 4) market states. We continue to find strong evidence of herding, as most of the herding coefficients are negative and statistically significant. This implies that herding occurs in either market state, with the exception of quartile 2, where investors appear to trade on private signals when the market is falling.

Table 5

Herding behavior in rising and declining stock market conditions.

This table presents the estimated coefficients of Eq. (10):

$$CSAD_t = \varphi_0 + \varphi_1 D\times\left|R_{m,t}\right| + \varphi_2(1-D)\times\left|R_{m,t}\right| + \varphi_3 D\times\left(R_{m,t}-\bar{R}_{m,t}\right)^2 + \varphi_4(1-D)\times\left(R_{m,t}-\bar{R}_{m,t}\right)^2 + \varphi_5 CSAD_{t-1} + \varepsilon_t$$

Panels A and B report the estimates of herding behavior in rising and declining stock market conditions for the overall market and size based quartile portfolios respectively. Each quartile in Panel B is constructed based on the closing annual market capitalization of the individual stocks listed on the TTSE. The quartiles are re-weighted each year, based on changes in the market capitalization of individual stocks listed in the market. Portfolio 4 is the largest size based quartile, while portfolio 1 is the smallest. $CSAD_t$ is the cross sectional absolute standard deviation (measure of return dispersion) and R_m is the equally weighted realized return of all (1) firms listed on the TTSE and (2) firms in each quartile. $\bar{R}_{m,t}$ is the arithmetic mean of $R_{m,t}$ and $CSAD_{t-1}$ is the 1-day lag variable of $CSAD_t$. D is a dummy variable that takes a value of 1 if $R_{m,t} < 0$ (declining market) and 0 otherwise (rising market).. The numbers in parenthesis are p-values. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	$D\times\left\|R_{m,t}\right\|$	$(1-D)\times\left\|R_{m,t}\right\|$	$D\times\left(R_{m,t}-\bar{R}_{m,t}\right)^2$	$(1-D)\times\left(R_{m,t}-\bar{R}_{m,t}\right)^2$	$CSAD_{t-1}$	*Chi-Square*	Adj-R^2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Market Portfolio							
TTSE	1.8913*** (0.000)	1.8381*** (0.000)	-0.0074*** (0.000)	-0.0174*** (0.003)	0.0074** (0.019)	17.924*** (0.000)	0.9735
Panel B: Sized Ranked Portfolios							
Quartile 4 (Largest)	1.8778*** (0.000)	1.4568*** (0.000)	-0.0436*** (0.000)	-0.0796*** (0.000)	0.0415*** (0.000)	2.3922 (0.121)	0.5928
Quartile 3	1.2917*** (0.000)	1.5383*** (0.036)	-0.0046 (0.102)	-0.0839*** (0.000)	-0.0134 (0.121)	41.983*** (0.000)	0.7963
Quartile 2	1.1273*** (0.000)	1.7617*** (0.000)	0.0907*** (0.000)	-0.1211*** (0.000)	-0.0197** (0.022)	91.793*** (0.000)	0.7168
Quartile1 (Smallest)	2.5045*** (0.000)	1.9671*** (0.000)	-0.0680*** (0.000)	0.3784*** (0.000)	0.0389*** (0.001)	113.76*** (0.000)	0.7237

A Wald test is used to check for asymmetries, by assessing whether the difference between φ_3 and φ_4 is statistically significantly different from zero. We present the chi-square statistics of this test in column (6), which shows that asymmetry is significant in the overall market and quartiles 3, 2 and 1. In most cases, herding is stronger during rising market states, with the exception of quartile 1, where herding is more prominent in declining markets.

Herding is stronger in rising conditions in the TTSE for the following possible reason. Rising markets are featured by greater investor confidence and optimism. In the TTSE, there is a greater tendency to trade on sentiment and overlook information on fundamentals, as investors are, in general, not sophisticated. Since investors are more optimistic in rising markets, they are therefore more likely to herd.

4.3. Time-varying herding

To gain more insights into herding behavior in the TTSE, we investigate time variations in herding over the sample period. Indeed, herding is not likely to be a static feature of markets, but evolves over time when there are changes in investor sentiments, the availability of information on fundamentals and when the market undergoes institutional and regulatory changes. Figure 1 plots the time varying estimates of the herding parameter φ_2 based on the state-space model.[8] It is clear from the figure that the extent of herding in the overall market and in each size-quartile varies with time, confirming that a constant coefficient approach does not completely and accurately capture herd behavior. The bulk of these time varying parameters are negative for the TTSE and each size-quartile, suggesting that herding is widely active over the sample period in the market and the various quartiles. In particular, for the TTSE, 3418 (95%) of the time varying parameters are negative while the mean parameter value is -0.571. Among the size quartiles, the degree of herding is most pronounced in quartile 2, as its mean is the lowest (most negative) at -1.976, while the tendency to herd is most evident in quartile 1 given that it has the highest number of negative coefficients, 3554

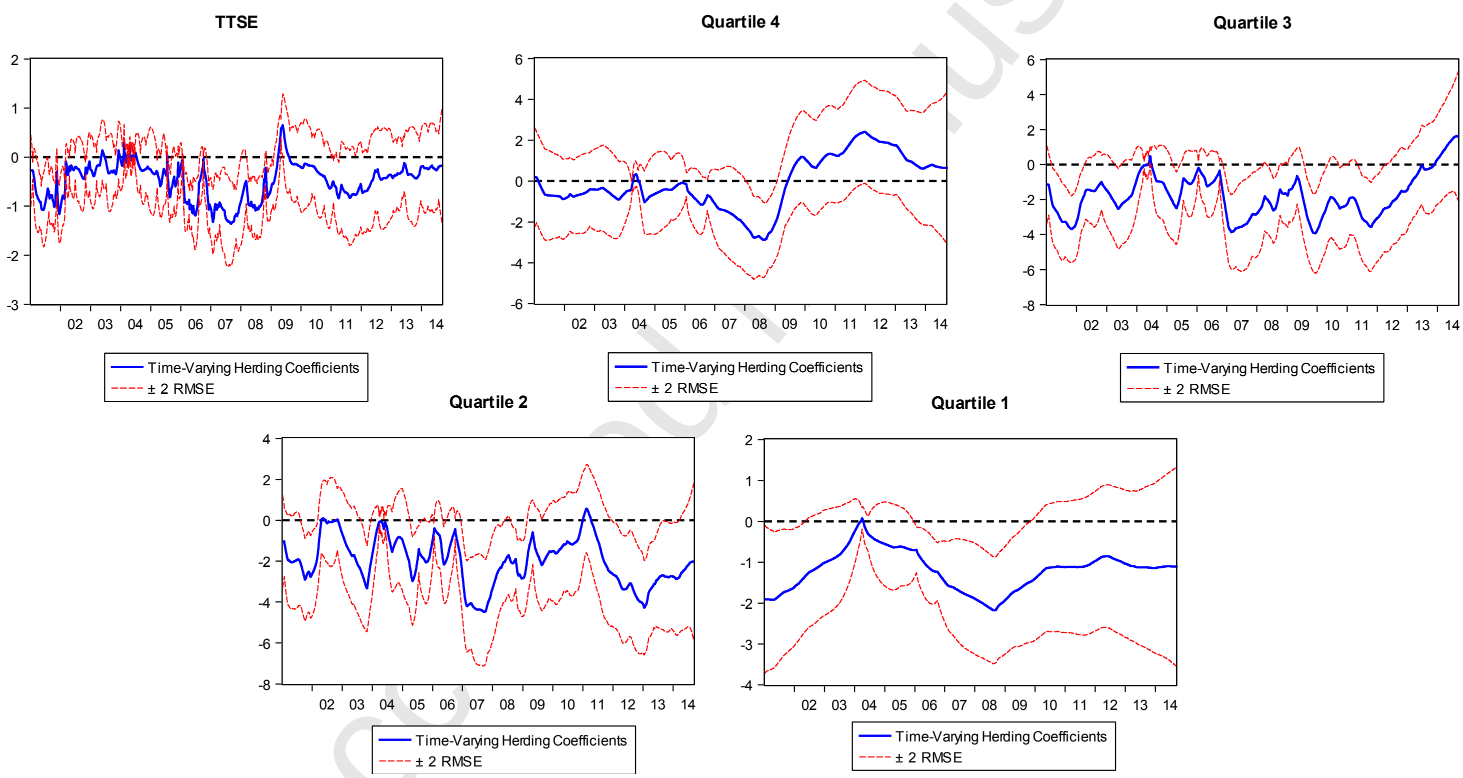
[8] We also present summary statistics of the time varying herding parameters in Table A1.

(99%). Quartile 4, however, has the least number of negative coefficients at 2118 (59%) and the highest mean of -0.092. It also exhibits the most variation in herding, having the largest standard deviation value of 1.294.

Figure 1

Evolution of Herding – TTSE and Sized-Based Quartiles

This figure plots the time series estimates of herding coefficients for the overall market and size based quartile portfolios.



Turning to the plot of the time-varying herding parameters for the TTSE in Figure 1, we observe a brief period of anti-herding behavior in 2004. Such a finding implies that for this interval, investor trading was mainly informed and not based on the actions of their peers or the market consensus. This is mirrored by each size-quartile for the same time period.

Herding, however, becomes more pronounced, over 2007 and 2008, across all quartiles and the overall TTSE, as reflected by the magnitude of the negative coefficients over this time. Such a finding is attributed to effects of the international financial crisis. As investors in this market are generally not sophisticated, they are more likely to suppress their own beliefs and mimic the trading behavior of others during times of high market stress and financial turmoil, rather than trading on fundamentals. This is also supported by Balcilar *et al.* (2013), Christie and Huang (1995) and Chang *et al.* (2000). In 2009, however, there appears to be anti-herding behavior in the TTSE. This finding may be associated with increased analyst coverage in the aftermath of the global financial crisis. Increased analyst coverage would have produced more public information on fundamentals. Investors were therefore able to base their trade decisions on private signals on fundamentals rather than the decisions of their peers. In addition, this period also witnessed the collapse of the largest financial conglomerate in Trinidad and Tobago, which had rippling effects throughout the economy. This caused the financial authorities, particularly the Securities and Exchange Commission of Trinidad and Tobago (SECTT), to mandate increased analyst coverage, company transparency and improvements in the information environment, thereby encouraging less herding. Quartile 4 appears to be the only quartile, which experienced anti-herding in 2009, and this lasted for the rest of the sample period. Since this quartile has the largest size, it is associated with greater information flows relative to the others. Investors who trade in the stocks which comprise this portfolio are less inclined to herd, which is more evident following the financial crisis, when more information on fundamentals were produced. Quartile 1, on the contrary, exhibits the most herding over the sample period. Indeed, this quartile is the smallest, and is therefore associated with less information flows with a greater portion of investors who trade on the sentiments of others rather than private signals.

4.4. Robustness checks

In this section we assess the robustness of our earlier results that liquidity and volatility increase herd behavior. For this purpose, we estimate the following regression:

$$Herd_t = \alpha + \delta_1 R_{m,t} + \delta_2 Liq_t + \delta_3 Vol_t + \delta_4 Vol_{JSE,t} + \delta_5 Herd_{t-1} + \varepsilon_t \tag{11}$$

The dependent variable $Herd_t$ is an indicator of daily herding, measured by the time-varying herding parameter (φ_2) derived from the state space model (Eq. 6 and 7) estimated earlier in the paper. We maintain the use of volume traded and GARCH (1, 1) variances as our measures of liquidity (Liq_t) and volatility (Vol_t) respectively. We also control for the stock market performance, measured by the stock market return ($R_{m,t}$) and volatility on the Jamaican Stock Exchange (JSE) denoted as $Vol_{JSE,t}$. Indeed, prior studies show that herding is correlated with stock market performance. Chang *et al.* (2000) and Qiao *et al.* (2014) find that herding increases when returns are increasing, while Lao and Singh (2011) find pronounced herding during periods of large market movements. It is also important to consider whether herding is influenced by volatility on the JSE, given that many stocks traded on the TTSE are also cross-listed on the JSE. Trinidad and Tobago and Jamaica are also connected through an economic union and share similar socio-economic characteristics. Therefore, market shocks, which give rise to uncertainties in the JSE, are likely to affect investors' trading decisions and behavior on the TTSE. $Vol_{JSE,t}$ is measured by the daily GARCH(1,1) variances estimated using the JSE market index. We also control for the lagged dependent variable $Herd_{t-1}$ to ensure that our results are not a spurious restatement of potential autocorrelation in the dependent variable.

Table 6 provides the estimates of regression Eq. (11) for the overall TTSE and each size quartile. Note that since the herding measure itself has a negative value, a negative coefficient suggests that the magnitude of herding improves as the respective variable increases. Again, the estimates for Liq_t and Vol_t in columns (1) and (2) are negative and statistically significant, with the exception of the liquidity coefficient for quartile 4. These estimates corroborate our previous findings for liquidity and volatility in tables 3 and 4 respectively, confirming that by and large, herding behavior on the TTSE is associated with higher liquidity and volatility. It is also observed that as returns rise, herding on the TTSE increases, suggested by the negative and statistically significant coefficients in column (3). This finding suggests that as the stock market performance increases, reflected by higher returns, investors are more inclined to discard their own private beliefs and trade in line with the market consensus. During such periods, we may therefore find investors placing a higher number of buy orders. When the market declines and suffers losses, however, investors may be less inclined to follow their peers and engage in sell orders. Herding, however, decreases with volatility in the JSE, as the coefficients in Column (5) are by and large positive and statistically significant. These results may be attributed to the behavior of investors who trade on both the TTSE and the JSE. Specifically, those investors may be more sophisticated, and therefore, when uncertainty in the JSE increases, as reflected in higher volatility, they are more likely to act independently and trade on fundamentals.

Table 6
Determinants of herding dynamics

This table presents the estimated coefficients of Eq. (11):
$Herd_t = \alpha + \delta_1 R_{m,t} + \delta_2 Liq_t + \delta_3 Vol_t + \delta_4 Vol_{JSE,t} + \delta_5 Herd_{t-1} + \varepsilon_t$
Panels A and B report the determinants of herding behavior for the overall market and size based quartile portfolios respectively. $Liq_{,t}$ is the liquidity variable and is measured by measured by the daily volume traded. Vol_t, is measured by the daily Generalized Autoregressive Conditional Heteroscedasticity (GARCH (1, 1)) variances. R_m stock market return. $Herd_t$ is an indicator of daily herding, measured by the time-varying herding parameter derived from the state space model. $Herd_{t-1}$ *is* a 1 day lag variable of $Herd_t$ and $Vol_{JSE,t}$ is measured by the daily GARCH(1,1) variances estimated using the JSE market index.

	Liq_t	Vol_t	R_m	$Herd_{t-1}$	$Vol_{JSE,t}$	Adj-R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Market Portfolio						
TTSE	-2.05E-11*	-0.0031***	-0.0055*	0.9990***	9.31E-05*	0.9980
	(0.050)	(0.000)	(0.091)	(0.000)	(0.076)	
Panel B: Sized Ranked Portfolios						
Quartile 4 (Largest)	1.69E-11*	-0.0034***	-0.0042**	0.9881***	0.0003**	0.9217
	(0.052)	(0.000)	(0.014)	(0.000)	(0.033)	
Quartile 3	-2.35E-11***	-0.0047***	-0.0034***	1.0007***	0.0002**	0.9993
	(0.045)	(0.000)	(0.000)	(0.000)	(0.038)	
Quartile 2	-4.44E-11	-0.0064***	-0.0134**	0.9971***	0.0014***	0.9965
	(0.202)	(0.013)	(0.034)	(0.000)	(0.000)	
Quartile 1 (Smallest)	-1.26E-10***	-0.0105**	-0.0115***	0.9976***	4.63E-05	0.9991
	(0.000)	(0.043)	(0.000)	(0.000)	(0.890)	

5.0 Conclusion

This paper examines herd behavior in a frontier market, the TTSE. Frontier markets have not only been popular with international investors for their possible diversification potential, but their unique characteristics provide a suitable setting for investigating herding. We are motivated by a paucity of studies on herd behavior in frontier markets and through this paper, attempt to make a contribution in terms of studying herding in the TTSE by using both a constant coefficient approach and a time-varying approach.

We find significant evidence of herding in the overall market. The analysis also considers herding in four sized based quartiles and finds that herding is prevalent in each quartile. The results show that in general, herding becomes progressively stronger as we move towards smaller stocks. This indicates that there is greater asymmetric information associated with smaller stocks.

Our findings further suggest that an increase in liquidity is associated with a greater incidence of herding. This indicates that greater liquidity may not foster the dissemination and use of information on fundamentals. Instead, it is a pointer towards irrational and sentimental behaviour of predominantly unsophisticated investors, who mimic the actions of other traders. Our results also indicate that as volatility increases, there is a greater tendency to engage in herding. Investors may be more prone to discard their own private information and skill sets to follow the market consensus during periods of risk and uncertainty. We however find that both liquidity and volatility appear to reduce herding in the largest size quartile, suggesting that investors in larger firms pay more attention to fundamentals and could be less irrational than investors in smaller counterparts. Further analyses show that herding in the TTSE occurs irrespective of market states, but is stronger during rising markets. It appears that rising markets infuse the investors with greater optimism, which then percolates to their trading activity *en-masse*.

Our time-varying analysis shows that herding evolves over time, implying that the constant coefficient approach can only offer partial information about such behaviour. Such results are expected, as investors' behaviours are dynamic and not always rational. Their sentiments, preferences and biases constantly change, along with economic fundamentals. We find significant evidence of time-varying herd behaviour across the TTSE and also through the four quartiles. We again confirm that herding tendency is more pronounced for the smallest quartiles. Brief time intervals appear (2004 and 2009) where there is anti-herding in the TTSE, while some other time segments (2007 and 2008) demonstrate greater herding. It follows that investors show a tendency to stick together during crisis periods (2007-2008), while a greater awareness, analyst coverage and access to information following the crisis tends to break the herd in 2009. The largest size-quartile continues to show anti-herding behaviour post 2009 till the end of the sample period. Robustness checks further support our findings that changes in the market environment and microstructures do indeed affect herd behaviour on the TTSE.

As the TTSE moves on its path to development, there have been regulatory and institutional steps to strengthen the level of public disclosure from the firms. There is more urgency to pursue better information exchange and analyst coverage. Such steps may reduce herding behaviour in the future.

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Appendix A

Table A1

Summary statistics for the time-varying herding coefficients

This table reports the descriptive statistics for the time-varying herding coefficients estimates, derived from the state-space Kalman-filter (Eq. 7), for the overall TTSE and each size based portfolio. The overall sample period is January 2001 to December 2014.

	Median	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Maximum	Minimum	Observations
TTSE	-0.490674	-0.571124	0.387332	-0.243978	2.628425	56.01775	0.556572	-1.547584	3574
Quartile 4 (Largest)	-0.414426	-0.092425	1.294727	-0.020036	2.392945	55.11731	2.404007	-2.883467	3574
Quartile 3	-1.875296	-1.763991	1.218035	0.443817	2.920751	118.2661	1.630289	-3.924942	3574
Quartile 2	-1.979712	-1.975616	1.155255	-0.109561	2.465785	49.64890	0.563200	-4.464884	3574
Quartile 1 (Smallest)	-1.114534	-1.190466	0.482858	0.011595	2.570965	27.49132	0.072419	-2.172695	3574