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Yilmaz Guney, Vasileios Kallinterakis, Gabriel Komba

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Herding in Frontier Markets: Evidence from African Stock Exchanges

Yilmaz Guney[a], Vasileios Kallinterakis[b,*] and Gabriel Komba[c]

[a] Business School, University of Hull, HU6 7RX, Hull, UK; Email: y.guney@hull.ac.uk
[b] University of Liverpool Management School, Chatham Building, Chatham Street, Liverpool L69 7ZH, UK; E-Mail: V.Kallinterakis@liverpool.ac.uk
[c] School of Business, Mzumbe University, P. O. Box 6, Mzumbe, Tanzania; Email: gkomba@mzumbe.ac.tz

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*Corresponding author: E-Mail: V.Kallinterakis@liverpool.ac.uk.

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Abstract

We investigate herding in eight African frontier stock markets between January 2002 and July 2015, given the limited evidence on herding in frontier markets. Herding appears significant throughout the 2002-2015 period for all markets, with smaller stocks found to enhance its magnitude. Herding entails no clear asymmetries conditional on market performance; conversely, it appears notably asymmetric when conditioned on market volatility, as it is significant (or stronger) mainly during low volatility days, without this pattern, however, surviving when accounting for the 2007-2009 crisis. The US and South African markets motivate herding on a small number of occasions only, while the return dynamics of a regional economic initiative's member-markets are found to induce herding in each other very rarely, thus demonstrating that investors' behaviour in markets with low integration in the international financial system is not significantly affected by non-domestic factors.

JEL classification: G01; G02; G15

Keywords: herding; frontier markets; asymmetric behaviour; Africa

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1. Introduction

Research in behavioural finance has produced ample evidence on the presence of herding internationally for a wide cross section of markets, both developed and emerging, and has demonstrated that the significance of herding is a function of a series of factors and market states (see the excellent reviews by Hirshleifer and Teoh, 2003 and Spyrou, 2013). It is interesting, however, to note that little is known about herding and its possible determinants in the category of markets formally known as "frontier", despite the increased attention they have received on behalf of international portfolio investors over the past decade as a result of the diversification benefits they offer, given their relatively low levels of correlation with international markets (Berger et al., 2011; De Groot et al., 2012).

Given the relatively limited research on frontier markets' herding and its determinants (Balcilar et al., 2013; 2014; Economou et al., 2015b), our study contributes in that direction by investigating herding in African frontier stock exchanges, addressing several research questions. First, we examine whether herding is significant in frontier markets in Africa and whether it presents us with size-effect, in view of the low trading activity and high market concentration typifying frontier markets in general. Second, in line with the extant herding literature, we investigate whether herding in a market exhibits asymmetric properties conditional upon the market's performance (positive/negative market returns) and volatility (high/low market volatility). Third, we test whether controlling for the return dynamics of the US (the world's largest market) and South Africa (the continent's largest and most developed financial market and key economic partner to most African economies) confers any effect over our estimated herding. Fourth, we explore the role of regional economic integration over our sample markets' herding, by testing whether the return dynamics of a regional economic initiative's member-markets motivate herding in each other. Finally, we assess the effect of the 2007-2009 global financial crisis by examining whether herding varies in its significance prior to, during and after its outbreak.

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To begin with, herding, as a behavioural trading pattern, has been regularly observed in stock exchanges throughout the centuries (see e.g., Corzo et al., 2014). From a theoretical viewpoint, herd behaviour arises in financial markets when investors discard their private signals and resort to copying each other's trades following interactive observation of the actions – or the payoffs of these actions – of their peers (Hirshleifer and Teoh, 2003). Herding can either be motivated by intent (*intentional herding*) or be the result of correlated responses of investors to factors they are commonly exposed to (*spurious herding*).[1] Investors herd intentionally when they expect to extract a benefit from such behaviour in the form of a positive externality (i.e., payoff). This payoff can be *informational*, in which case investors track their peers' trades in order to free-ride on their information, because they consider their peers' information (or information-processing skills) to be of superior quality (Devenow and Welch, 1996). In the extreme, if investors herd on the information of others while suppressing their own private signals, this will prevent the latter from being incorporated in the public pool of information, leading prices in the market to be shaped by limited information and rendering the creation of informational cascades (Banerjee, 1992; Bikhchandani et al., 1992) more likely. The anticipation of *professional* payoffs can also motivate herding intent, particularly among investment professionals, such as fund managers, whose performance is assessed regularly (normally every quarter) on a relative basis, i.e. versus the performance of their peers. In that case, fund managers of low ability would be strongly motivated to copy the trades of their high-ability counterparts in order to boost their professional reputation and secure their career-prospects (Scharfstein and Stein, 1990). Turning now to spurious herding, investment professionals can exhibit correlation in their trades as a result of *relative homogeneity*, which is normally manifested through their similar educational/professional qualifications (De Bondt and Teh, 1997), the similar indicators they employ in their analyses (Froot et al., 1992; Hirshleifer et al., 1994) and the common regulatory framework reigning their professional conduct (De Bondt and Teh, 1997; Voronkova and Bohl, 2005; Olivares, 2008). Another source of spurious herding in the market is *characteristic trading* ("style investing"), which refers to any strategy basing stock-selection on specific stock characteristics (such as past

[1] For a detailed discussion on the intentional-spurious typology of herding, see Bikhchandani and Sharma (2001), Holmes et al. (2013), Gavriilidis et al. (2013) and Galariotis et al. (2015).

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performance, sector and size) and is rather popular among institutional investors (Bennett et al., 2003). If a large number of funds, for example, pursue momentum strategies, then one would expect them to be going long on recent winners and short on recent losers, thus leading their trades to exhibit correlation without the latter being the outcome of imitative intent.

A vast amount of research has studied herding empirically in a multitude of markets, both developed and emerging, with evidence to date denoting the presence of several patterns internationally. Size, for example, has been widely documented as being a key determinant of herding, with the significance of the latter being encountered mostly among stocks of the smallest[2] (Lakonishok et al., 1992; Wermers, 1999; Sias, 2004; Wylie, 2005; Hung et al., 2010) and the largest[3] (Wylie, 2005; Kremer and Nautz, 2013) capitalization segments. Another key determinant of herding is industry, with evidence suggesting the presence of various industry-herding patterns internationally (Choi and Sias, 2009; Zhou and Lai, 2009; Demirer et al., 2010; Gavriilidis et al., 2013; Gebka and Wohar, 2013). Herding has been shown to display asymmetries in its significance conditional upon different market states (although these asymmetries are far from uniform internationally)[4], while evidence also suggests that financial crises represent turning points for herding evolution.[5] Evidence also exists suggesting that US return-dynamics induce herding internationally (Chiang and Zheng, 2010), while the return-dynamics of cross border exchanges' largest member-markets produce herding in their smaller

[2] Small capitalization stocks enjoy limited analyst following, the result being that information about them is normally less, both in amount and precision; to tackle this informational predicament, an investor holding positions in small stocks could opt for monitoring his peers' trades as an additional source of information. What is more, the high information risk surrounding small stocks increases their liquidity risk; since their overall visibility in the market is low, investors' attention towards them is limited, rendering small stocks less liquid. As a result, investors would be motivated to herd with their peers when trading small stocks, since, the rising volume generated by herding would help increase the likelihood of their orders being timely executed.

[3] Herding towards large stocks is mainly motivated by professional reasons, which, in turn, are mostly relevant to investment professionals. Evidence (Voronkova and Bohl, 2005; Olivares, 2008) has indicated, for example, that pension funds' managers in emerging markets face regulatory restrictions in their stock-selection, leading their investments to be biased towards their domestic markets' largest capitalization stocks. Walter and Weber (2006) also showed that strong herding in large cap stocks may be a reflection of what they called "benchmark herding", the latter referring to fund managers biasing the composition of their portfolios towards the constituent stocks of the index against which their performance is benchmarked in order to avoid underperforming it. Since blue chip indices represent the most popular benchmarks for this purpose, "benchmark herding" constitutes another possible explanation underlying herding towards large stocks.

[4] Overall, there seems to be a tendency for herding to grow more significant during periods characterized by negative market performance (Goodfellow et al., 2009; Zhou and Lai, 2009; Demirer et al., 2010; Economou et al., 2011; Holmes et al., 2013; Gavriilidis et al., 2013), low volatility (Economou et al., 2011; Holmes et al., 2013), low volume (Tan et al., 2008; Economou et al., 2011) and optimistic sentiment (Liao et al., 2011). Several studies (Chang et al., 2000; Caparelli et al., 2004) have failed to detect herding asymmetries conditional upon market performance, while others (Chiang and Zheng, 2010; Chiang et al., 2010) have produced mixed evidence in that respect.

[5] Some studies (Kim and Wei, 2002; Chiang and Zheng, 2010; Mobarek et al., 2014) have reported increased herding following the outbreak of financial crises, while others (Choe et al., 1999; Hwang and Salmon, 2004) found that herding tends to decline post crises' outbreak.

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member-markets (Economou et al., 2015a). Overall, herding has been found to be relatively stronger in emerging markets compared to developed ones, a fact that has been attributed to emerging markets' lower transparency, which renders their informational environment more ambiguous, thus prompting investors to resort to herding as a means of resolving this ambiguity (Gelos and Wei, 2005).[6]

An issue arising from the above discussion is that, unlike for developed and emerging markets, there appears to be very little research undertaken on herding in frontier markets. This issue is worth noting, given the recent surge in international portfolio investments in these markets during the past decade, reflected through the rising number of mutual funds and exchange traded funds launched with an explicit focus on frontier market equities (Berger et al., 2011; De Groot et al., 2012). Much of this interest stems from the low correlations of frontier markets with global markets (Alagidede, 2009) which confer diversification benefits to international investors including frontier markets' stocks in their portfolios (Goetzmann et al., 2005; Speidell and Krohne, 2007; Berger et al., 2011). Overall, frontier markets represent a notably heterogeneous set of markets, yet share - to varying degrees - some common features. Most frontier markets' economies are characterized by low labour costs and a labour force of improving skills, both of which have rendered these countries key destinations for the outsourcing of production activities from higher-cost countries, while many of them are also major world exporters of several key agricultural goods and natural resources[7] (Speidell, 2011). The above have allowed frontier markets to enjoy high growth rates, which appear sustainable for the future (Behar and Hest, 2010), given these countries' early stage of development and the fact that most of them have been experiencing relatively stable social and political conditions over the recent past compared to previous decades of instability (Speidell, 2011). Furthermore, the booming demographics

[6] Herding has been found to be stronger in emerging markets compared to developed ones. Fund managers, for example, tend to exhibit significantly higher levels of herding in Portugal (Holmes et al., 2013), South Korea (Choe et al., 1999) and Taiwan (Chang, 2010; Lu et al., 2012), 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; Choi and Sias, 2009). Evidence from frontier markets (Economou et al., 2015b) has shown that they also accommodate substantial institutional herding, whose levels are significantly higher compared to those documented in emerging markets. The picture remains similar when assessing herding at the aggregate market level. Chang et al. (2000) showed that market herding was significant in the two emerging markets of their sample (South Korea; Taiwan), contrary to the developed ones (US; Hong Kong; Japan); Demirer et al. (2010) reported significant market herding for Taiwan, while strong market herding has also been reported for Chinese markets (Tan et al; 2008; Chiang et al., 2010). With regards to frontier markets, Balcilar et al. (2013; 2014) have presented evidence indicating significant market herding in Gulf Arab stock exchanges.

[7] Seven out of the top ten world producers of oil and half of the top ten natural gas producers are frontier economies from the Gulf, Central Asia and Africa. Major exporters of several minerals (e.g. copper, lead, nickel, zinc) and agricultural products (e.g. cocoa, coffee, sugar, tea) are also frontier countries (Speidell, 2011).

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of their populations (large sections of which are under age 15) and the rising per capita income levels point towards a gradual rise in living standards and suggest a considerable growth potential for several sectors (such as banking and information technology, whose levels of penetration in their local populations are currently moderate) and a greater diversification of their economic activity (Speidell, 2011). This is also expected to have important implications for the development of their financial markets, which are currently characterized mainly by incomplete and ill-enforced institutional frameworks, with low transparency levels (Economou et al., 2015b). These conditions at present tend to deter investors (be they local or foreign) from participating in these markets, the result being that most frontier equity markets are small, very highly concentrated and illiquid, with very low levels of capitalization and trading volume (Marshall et al., 2015). As a result, the trading environment in frontier stock exchanges introduces impediments in both the generation (given the low investors' participation and trading activity) and quality (due to the low transparency) of information.

It would thus be expected that investors would be less prone to rely on fundamentals and more likely to resort to herding, since monitoring the trades of other investors would help them infer potentially useful information; however, the very small amount of research undertaken on herd behaviour in frontier markets to date essentially renders our knowledge on this issue rather limited. Balcilar et al. (2013) found that herding in the frontier stock exchanges of Gulf Arab states is significant, with market volatility constituting a key determinant of its significance; Balcilar et al. (2014) confirmed these results, while further reporting evidence suggesting an effect of global factors (such as US market performance and oil prices) over the evolution of herding in these markets. Using quarterly portfolio-holdings reports from funds in Bulgaria and Montenegro, Economou et al. (2015b) demonstrated that institutional herding in both these markets was significant and intentional, motivated by informational and professional reasons.

In view of the limited amount of studies on frontier markets' herding, our study contributes to research on this issue by examining herding in eight African frontier stock exchanges (BRVM[8];

[8] BRVM is the abbreviated form of "Bourse Régionale des Valeurs Mobilières" (Regional Securities Exchange), which is a cross border exchange established in 1998 by the eight member-states of the West African Economic and Monetary Union (Benin, Burkina Faso, Guinea Bissau, Ivory Coast, Mali, Niger, Senegal and Togo).

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Botswana; Ghana; Kenya; Namibia; Nigeria; Tanzania; Zambia) for the January 2002 – July 2015 period. Given the research questions our work addresses (and which were outlined earlier in this section), our results can be summarized as follows. Investors herd in all eight markets, something that can be ascribed to the low transparency levels prevailing in frontier stock exchanges that reduce the quality of their informational environment, leading investors to resort to herding as a means of inferring information by tracking their peers' trades. Smaller stocks amplify the magnitude of herding, since the latter grows larger for equal- (compared to value-) weighted estimations, something hardly surprising, given the greater informational uncertainty surrounding smaller stocks that prompts investors to herd more when trading them. Herding is not found to exhibit significant asymmetries conditional on market returns, as it appears significant irrespective of the market's directional movement in most cases. On the other hand, herding appears significant (or stronger, compared to high volatility days) mainly during days of low volatility, with this asymmetric pattern, however, growing weak when partitioning our sample period to account for the 2007-2009 global financial crisis. Although "domestically" motivated herding is significant across all eight markets, the same cannot be argued for herding induced by the US and South African market returns, the presence of which is confirmed on only a small number of occasions; similarly, the return dynamics of a regional economic initiative's member-markets are found to motivate herding in each other very rarely. These results are very interesting, as they indicate that investors' behaviour in African frontier markets is not significantly affected by non-domestic factors and are in line with extant research denoting the overall low levels of integration of frontier markets within the global financial system.

Our study makes the following four contributions to the literature. First, it produces evidence on the presence of herding in African frontier stock exchanges, thus allowing novel insights on herding in frontier markets, to which very little research has been devoted. Second, we demonstrate that herding in African frontier markets is subject to the effect of determinants similar to those reported for developed and emerging markets in earlier research, particularly size-effect and - to a lesser extent – market volatility (for the full sample period only) and US market returns. Third, we show for the first time in the literature that frontier markets' herding can be motivated, albeit to a limited extent, by

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their continent's key stock exchange (in our case, South Africa). Fourth, the fact that the return-dynamics from the US, South Africa and regional economic initiatives' member-markets motivate herding to a limited extent in our sample markets helps showcase that investors' behaviour in markets with low integration in the international financial system is not significantly affected by non-domestic factors.

The issues explored in this study are relevant to several parties with an interest in frontier markets, including these markets' regulatory authorities, investors holding (or planning to hold) positions in frontier markets and researchers with a focus on this market category. The findings reported in this paper are of particular relevance to international portfolio investors, as they suggest the presence of herding patterns which can help inform their equity trading in frontier markets. Considering the relatively opaque informational environment typifying these markets, any insight pertaining to their investors' behavioural patterns can confer informational benefits to overseas investors by providing them with actionable knowledge (they can, for example, incorporate observed herding patterns in their strategies). From a regulatory viewpoint, the significant herding documented in African frontier markets suggests that measures aiming at containing it are necessary in order to prevent the occurrence of destabilizing outcomes as a result of it; regulators in these markets, for example, can consider measures geared towards enhancing transparency (e.g., stricter and stringently enforced disclosure requirements, in line with international financial reporting standards) and investors' trust (e.g. better monitoring and more severe punishment of manipulation and insider trading). What is more, the fact that the dynamics of the US and South Africa can incite herding in some of Africa's frontier markets should be of key interest to these markets' regulators, since it suggests that these dynamics should be monitored more carefully as possible early warning signals of herding in their markets, in order to avoid potentially destabilizing incidents. From a research perspective, the fact that South Africa is found to motivate herding in some of our sample markets indicates for the first time in the literature that a continent's lead market can be an important herding determinant for some of the continent's other markets, thus denoting an alternative source of herding for future research.

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The rest of the paper is structured as follows. Section 2 introduces the empirical design employed to test for our research questions and presents the data utilized, alongside some descriptive statistics. Section 3 presents and discusses the results, while section 4 provides a summary and conclusion.

2. Data and Methodology

Our data includes daily observations on closing prices and market capitalization values for the period between January 23rd, 2002 and July 15th, 2015[9] for all common stocks listed on the following eight African equity markets: BRVM, Botswana, Ghana, Kenya, Namibia, Nigeria, Tanzania and Zambia; all data was obtained from the Thomson-Reuters DataStream database. To mitigate the possibility that survivorship bias is present in our sample, the latter includes data both on currently active stocks, as well as stocks that have been delisted or suspended throughout the sample period.

Empirical approaches aiming at detecting herding on the premises of price-data have long relied on the assumption that herding is identified with a reduction in the cross sectional dispersion of securities' returns, the latter taken to imply a clustering of stock returns around the market average, a reflection of the market's consensus. Christie and Huang (1995) first tested for this formally through the following empirical specification:

$$CSSD_t = \beta_0 + \beta_1 D_t^{UP} + \beta_2 D_t^{DOWN} + \varepsilon_t \qquad (1)$$

The dummy D_t^{UP} takes the value of one if the market return falls in the extreme-upper tail of the market return distribution, zero otherwise; conversely, the dummy D_t^{DOWN} equals one if the market return rests in the extreme-lower tail of that distribution, zero otherwise. As per CSSD, it represents the cross sectional standard deviation of returns, calculated as follows:

[9] The choice of the sample period here was motivated by the fact that we wanted a start-date early enough to allows us a window as long as possible, while at the same time having a pre crisis window of good length. We could have added other African frontier markets (such as Uganda and Zimbabwe) in the sample, yet their data were available only since early 2009 on the Thomson-Reuters DataStream database; had we included these markets in the sample as well, its start-date would have been pushed to early 2009 (to ensure consistency in our tests across markets), thus allowing us to work on the premises of a truncated sample window (2009-2015 in that case). With Nigeria furnishing us with data since January 23rd, 2002, no other market (aside from Uganda and Zimbabwe) having data starting afterwards and all other markets having data since the late 1990s, we chose to use the 23rd of January 2002 as the start-date.

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$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{n-1}} \tag{2}$$

$r_{i,t}$ is the return (calculated as the first logarithmic difference of closing prices) of security i on day t, $r_{m,t}$ is the equal-weighted average return of all active securities on day t and n is the number of traded stocks on day t. Since the different sensitivities of stocks to market movements imply a positive relationship between the cross sectional deviation of stock returns and absolute market returns (Black, 1972), the realization of extreme (be they positive or negative) returns by the market would lead to a rise in the cross sectional deviation of returns; in that case, herding would be absent and this would be reflected through significantly positive values for the dummy variables' coefficients (β_1 and β_2) in Equation (1). Conversely, if herding were to be present and give rise to extreme (positive or negative) market returns, the cross sectional deviation of returns would be expected to decline. This is because in that case investors would track the overall market consensus, while discarding their private signals, leading stock returns to cluster more around the average market return; in that case, we would expect β_1 and/or β_2 (depending on whether it is during extreme positive or extreme negative market returns that herding is significant) to assume significantly negative values. A key drawback of the Christie and Huang (1995) approach is that it attempts to capture herding through a linear empirical specification (based on the linear relation between the cross sectional deviation of returns and market returns); however, research[10] has demonstrated that herding is associated with non linear dynamics in capital markets that cannot be accounted for by a linear model, something further illustrated by the near-complete lack of evidence in favor of herding from studies[11] testing for it using the Christie and Huang (1995) model.

To test for herding in the presence of non linear dynamics, Chang et al. (2000) introduced an empirical specification including the possibility for non linearity in the relationship between the cross sectional deviation of returns and the market return, which is the following:

[10] See, for example, Lux (1995) and Focardi et al. (2002).
[11] See, for example, Christie and Huang (1995), Chang et al. (2000), Caparelli et al. (2004), Gleason et al. (2004), Demirer and Kutan (2006) and Demirer et al. (2010).

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$$CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t \tag{3}$$

Chang et al. (2000) proxy for the cross sectional deviation of returns via CSAD, which is the cross sectional absolute deviation of returns, not the CSSD used by Christie and Huang (1995); the reason for this is that the presence of extreme observations in a sample (i.e. outliers) can lead the CSSD to appear biased (Economou et al., 2011). Formally, the CSAD is calculated with the following formula:

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{N}\left|r_{i,t} - r_{m,t}\right| \tag{4}$$

The notation in Equation (4) is identical to that in Equation (2). Given rational asset pricing expectations, a positive relationship between the cross sectional deviation of returns and absolute market returns would be reflected in significantly positive values for β_1 and insignificant ones for β_2 in Equation (3) (Chang et al., 2000). If, however, herding were to give rise to extreme market returns, then the relationship between the cross sectional deviation of returns and absolute market returns would (as per our previous discussion) be negative and cease being linear, becoming non linear instead (Chang et al., 2000). In that case, β_2 would be expected to be significantly negative, revealing the presence of herding.

Equation (3) is used to test for the presence of herding in our eight sample markets; however, an issue with the CSAD-specification used there is that it is equal-weighted and, hence might be driven by the returns of smaller capitalization stocks. To control for the presence of size-effects in herding (and in view of our earlier discussion on the role of size in the significance of herding), we also estimate Equation (3) using the value-weighted versions of CSAD and $r_{m,t}$, calculated as follows:

$$CSAD_t = \sum_{i=1}^{N}\left|w_{i,t} r_{i,t} - r_{m,t}\right| \tag{5}$$

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t} r_{i,t} \tag{6}$$

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In Equations (5) and (6), the calculations are performed weighting the return ($r_{i,t}$) of each stock by its weight ($w_{i,t}$); the latter is the fraction of a stock's market capitalization on day *t* divided by the sum of the market capitalizations of all *n* traded stocks on day *t*.

As herding has been found to present itself asymmetrically contingent upon the state of the market, we test for herding asymmetries for each market conditional on two market variables, namely market returns and market volatility.[12] Regarding market returns, research (Goodfellow et al., 2009; Zhou and Lai, 2009; Demirer et al., 2010; Economou et al., 2011; Holmes et al., 2013; Gavriilidis et al., 2013) has shown that herding tends to become more significant during down-markets, something that has been ascribed to investors' risk-aversion. Faced with an increased likelihood of losses during market slumps, investors can herd on the sell-side with the rest of the investors in order to sell as early as possible and curtail their losses. Regarding fund managers, less skilled ones can copy the trades of their better skilled peers during down-markets and then blame any losses they realize on the adverse market movements, while at the same time claim that they made the right investment decisions (essentially the ones they copied from their "good" peers), thus concealing their true abilities. Bullish markets can also boost herding, since the euphoria permeating them can fuel optimistic sentiment among investors and, with prices rallying, this can prompt them to base their trading decisions more on their peers' trades (in order to avoid falling behind[13]) and less on their own private information (Economou et al., 2015a).

We test empirically for asymmetric herding conditional on market returns using Equation (7):

$$CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP})r^2_{m,t} + \varepsilon_t \tag{7}$$

In Equation (7), D_t^{UP} is a dummy variable assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$).

[12] As mentioned previously, herding asymmetries have been found to exist also with respect to volume and sentiment; however, we found no sentiment indicator at the daily frequency for any of our sample markets, while the availability of volume-data for the latter was limited, hence we are not testing for asymmetric herding based on those variables.

[13] This argument is relevant to Abel (1990)'s external habit formation model proposed as an explanation for the equity premium puzzle. According to that model, the utility of an individual depends not on their absolute level of consumption, but rather on how their consumption fares compared to the consumption of others. In the context of our argument here, an individual witnessing other investors entering a bullish market and realizing positive returns on their investments will feel tempted to follow suit and enter the market as well in order to profit like his counterparts.

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Herding can manifest itself asymmetrically conditional upon market volatility, with evidence (Economou et al., 2011; Holmes et al., 2013; Economou et al., 2015b) suggesting that low-volatility periods encourage investors to herd; this is based on the assumption that less volatile conditions render it easier for investors to observe the trades of their peers and herd on them. On the other hand, highly volatile conditions can also promote herding (Gavriilidis et al., 2013), if volatility is the result of a rise in information-flow; in that case, uninformed investors can track the trades of their informed peers to free-ride on their information. Highly volatile conditions can also induce herding due to the enhanced uncertainty they entail (the market environment grows more complex), thus encouraging investors to mimic their peers in order to reduce this uncertainty (Economou et al., 2015b).

We test empirically for asymmetric herding conditional on market volatility using Equation (8):

$$CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH}) r^2_{m,t} + \varepsilon_t \quad (8)$$

In Equation (8), D_t^{HIGH} is a dummy variable assuming the value of unity during high volatility days, and zero during low volatility days. Volatility here is measured using the squared value of daily market returns ($r_{m,t}$); in line with Economou et al. (2011) and Tan et al. (2008) we define high (low) volatility days as those for which volatility is higher (lower) than its previous 30-day moving average.

In the contemporary financial environment where the process of globalization has been under way since the 1990s, it is reasonable to expect that investors' behaviour in a market is subject to the effect of global factors; in the case of international equity markets, the performance of the US stock exchange – the world's dominant equity market - inevitably constitutes a key factor affecting their movement (Masih and Masih, 2001). Specifically with respect to herding, evidence indicates (Chiang and Zheng, 2010) that US market returns are capable of fomenting herding internationally. Given the gradual inclusion of frontier markets' equities in foreign investors' portfolios (Berger et al., 2011; De Groot et al., 2012) and the fact that this helps enhance these markets' global financial integration, we test for the effect of the US market over African frontier markets' herding using the following specification, in line with Chiang and Zheng (2010):

$$CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t \quad (9)$$

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In Equation (9) $r^2_{US,t}$ denotes the squared returns of the US market, the latter proxied here through the S&P 500 index.

At the continental level, the Johannesburg Stock Exchange (JSE) is Africa's largest in terms of both trading activity and market capitalization; accounting for 38 percent of all Sub Saharan African listed firms and 83% of Sub Saharan African market capitalization (Masetti, 2013), JSE constitutes Africa's leading financial market. In that capacity, JSE has, for decades, been at the forefront of initiatives aiming at enhancing integration and cooperation among African stock exchanges, including bi-directional cross-listings (of JSE-listed firms on other African stock exchanges and firms from other African countries on JSE) and sharing its financial infrastructure with other exchanges in the region (Adelegan, 2008). Despite the overall low levels of financial integration among African markets (Alagidede, 2009), research indicates that returns and volatility in some of them are affected by JSE's returns (Piesse and Hearn, 2005; Kambadza and Chinzara, 2012); as a result, the performance of the South African market could bear an effect over investors' behaviour in African stock exchanges, more so considering the fact that South Africa is a key trading partner of most African economies (Schaffnit-Chatterjee, 2013). Similar to Equation (9) above, we test for the effect of the South African market over African frontier markets' herding using the following specification:

$$CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t \quad (10)$$

In Equation (10) $r^2_{SA,t}$ denotes the squared returns of the South African market, proxied here through the FTSE/JSE All Share index; data on the daily closing values of the S&P500 and the FTSE/JSE All Share indices were obtained from Thomson-Reuters DataStream. In Equations (9) and (10), significantly negative values of β_2 would indicate the presence of significant, "domestic" herding, while if β_3 is significant and negative, this would indicate that the US/South African market also motivates herding in the market tested.

Economic integration has been found (Dornbusch et al., 2000) to enhance the correlation among markets, as it helps strengthen their economic and trade links, thus rendering their fundamentals more interlinked; however, no research to date has investigated the role of economic integration over

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herding in the integrated economies' stock exchanges.[14] To that end, and in view of several regional economic initiatives in the African continent, we test for the effect of regional economic integration over herding by assuming three of those initiatives relevant to our sample. These are the East African Community (EAC), the Economic Community of West African States (ECOWAS) and the Southern African Customs Union (SACU)[15] and based on those, we group our sample markets as follows: EAC (Kenya; Tanzania); ECOWAS (BRVM; Ghana; Nigeria); SACU (Botswana; Namibia).

For each market in a group, we estimate the effect over its herding of each of the other member-market's return dynamics using the following specification:

$$CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{n,t} + \varepsilon_t \qquad (11)$$

Similar to Equations (9) and (10), significantly negative values of β_2 would indicate the presence of significant, "domestic" herding in market *m*, while if β_3 is significantly negative, this would indicate that herding in market *m* is also motivated by the return dynamics of member-market *n*.

Finally, we test for the effect of the 2007-2009 global financial crisis by repeating all of the above estimations before, during and after the crisis' outbreak. The pre crisis period begins in January 23rd, 2002 (our sample's start-date) and ends on the 9th of October 2007, when the Dow Jones Industrial Average (DJIA) index reached its peak at 14,164.53 units. The crisis period begins from the 10th of October 2007 - when the DJIA index started showing its first descending signs - and ends on the 6th of March 2009, when the index reached its bottom at 6,443.27 points. With regards to the post crisis period, it starts from the 7th of March 2009 and lasts until the end of our sample period (July 15th, 2015).

Panel A in Table 1 presents some descriptive statistics on the equal- and value-weighted versions of the CSAD and $r_{m,t}$ for all eight markets of our sample. Overall, all average $r_{m,t}$ values are positive, reflective of a positive market performance of African frontier markets during the 2002-2015 period;

[14] The impact of financial integration over herding, on the other hand, has been examined by Economou et al. (2015a), whose evidence suggested that herding rose in significance in Euronext's all four member-markets (Belgium; France; the Netherlands; Portugal) following their merger into the Euronext cross border exchange.

[15] The EAC currently consists of Burundi, Kenya, Rwanda, Tanzania and Uganda and has been in force since 2000. The ECOWAS consists of Benin, Burkina Faso, Cape Verde, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone and Togo and has been in force since 1975. SACU dates back to 1910 and consists currently of Botswana, Lesotho, Namibia, South Africa and Swaziland.

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the largest average market return both for the equal- and value-weighted specifications is observed for the Tanzanian market, with the smallest equal-weighted (value-weighted) average market return reported for the Nigerian (BRVM) market. The most volatile $r_{m,t}$ values are observed for Zambia (equal-weighted) and Ghana (value-weighted), as the standard deviations of $r_{m,t}$ denote; conversely, $r_{m,t}$ is the least volatile in the BRVM (Botswana) for the equal- (value-) weighted $r_{m,t}$ values. Again here, we notice that the standard deviations of value-weighted $r_{m,t}$ are higher than those of their equal-weighted counterparts in all cases, thus suggesting that accounting for size renders the average market return more volatile; given the positive relationship between volatility and volume (Karpoff, 1987), it is possible that this is due to the fact that large capitalization stocks (whose volumes are higher) are more heavily weighted in value-weighted $r_{m,t}$, thus rendering their values more volatile. As per the CSAD, its highest average values are observed for Nigeria (Ghana) for the equal- (value-) weighted case, with the smallest values detected in Botswana (Tanzania) for the equal- (value-) weighted CSAD-versions. CSAD is most volatile (its standard deviation is the highest) in Zambia (Ghana) when calculated based on its equal- (value-) weighted version; it appears least volatile for the BRVM (Tanzania) for equal- (value-) weighted calculations. Overall, value-weighted CSADs bear higher average (standard deviation) values compared to their equal-weighted equivalents, with the exceptions of Tanzania and Zambia (Botswana, Tanzania and Zambia).

To gain additional insight into the return dynamics of our sample markets, we performed a Ljung-Box portmanteau test on the autocorrelation structure of their equal- and value-weighted $r_{m,t}$ values for ten lags, with results reported in panel B of Table 1. All LB test-statistics are statistically significant (1 percent level), denoting the presence of temporal dependencies in the first moment of returns and suggesting that our sample markets entail inefficiencies in their return-generating process (something expected for frontier markets, given their early stage of financial development; see Speidell, 2011). This is more pronounced for the equal-weighted $r_{m,t}$ values, whose LB test-statistics tend to be (with the exceptions of Botswana and Tanzania) higher than those of the value-weighted ones.[16]

[16] A possible explanation for this is that value-weighted market returns are shaped by the returns of larger stocks, which are more heavily traded and less affected by thin trading, thus reducing the potential for predictability in the structure of market returns in the value-weighted version of the latter.

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Given the low correlation frontier markets tend to exhibit with international markets (Alagidede, 2009) – and in view of the fact that we test for the effect of the US and South African market returns over our sample markets' herding - we present the correlations between each of our eight sample markets' (equal- and value-weighted) $r_{m,t}$ and the US (proxied here through the S&P500 index) and South Africa (proxied here through the FTSE/JSE All Share index) market returns for the full sample period (panels C and D) and the crisis period (identified with the 10/10/2007 – 6/3/2009 window; see panels E and F). Overall, Namibia presents us with the highest correlation coefficients in all four panels, with its highest correlations being those with South Africa.[17] The lowest correlations for the full sample period with the US (South Africa) are detected in Nigeria for both the equal- and value-weighted $r_{m,t}$ (Tanzania for the equal- and Zambia for the value-weighted $r_{m,t}$); the lowest correlations for the crisis period with the US (South Africa) are detected in Botswana for the equal- and Zambia for the value-weighted $r_{m,t}$ (Zambia for both the equal and value-weighted $r_{m,t}$). All in all, the correlations documented in panels C-F are in most cases very low (49 of the 64 coefficients of correlation reported are below 0.1), thus confirming extant evidence on the low integration frontier markets maintain with the international financial system.

Figure 1 presents graphs with the evolution of each of our sample markets' main index during our sample period.[18] For each market, we opted for the main and oldest possible domestic equity index; where that was not possible (due e.g. to unavailability of a domestic equity index covering our full sample period), we selected its S&P BMI designated index. As Figures 1 (a) to (g) show, the trend across all eight markets appears to be an ascending one throughout the period, with marked differences in each market's index-evolution.

[PLEASE INSERT FIGURE 1 HERE]

[PLEASE INSERT TABLE 1 HERE]

3. Results and Discussion

[17] This may partly be explained by the fact that Namibia's stock exchange is closely linked institutionally with South Africa's, being in partnership with Johannesburg Stock Exchange (JSE).

[18] No index at all was available since January 2002 (the start of our sample period) for Tanzania, hence its graph (Figure 1 (g)) is based on the Dar es Salaam index for which data is available since December 15th, 2006 (the earliest possible index for Tanzania on Thomson-Reuters DataStream), hence covering a shorter period compared to the rest of the markets.

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We begin with the presentation in Tables 2 (panel A) and 3 (panel A) of the results from the estimation of Equation (3) using both its equal- and value-weighted versions[19] for each of our eight sample markets for the full sample period. β_1 furnishes us always with significantly[20] positive values, in line with theoretical expectations regarding the positive relationship between the cross sectional dispersion of returns and absolute market returns. β_2 assumes significantly negative values for all tests (with the exception of the value-weighted one for Tanzania), denoting the presence of significant herding for our eight sample markets, something rather unsurprising, considering the fact that frontier markets tend to constitute relatively opaque informational environments, which tacitly encourage investors to resort to herding in the absence of reliable public information (see e.g. Economou et al., 2015b). Perhaps more interestingly, herding (with the exception of the aforementioned value-weighted test for Tanzania) appears stronger for equal-weighted estimations (their β_2 values are larger in absolute terms compared to those from value-weighted ones). This suggests that smaller stocks enhance the magnitude of herding in our sample markets, possibly due to smaller stocks suffering from greater informational uncertainty, which, in turn, prompts investors to imitate their peers more strongly when trading them (Lakonishok et al., 1992; Wermers, 1999; Sias, 2004; Wylie, 2005; Hung et al., 2010).

[PLEASE INSERT TABLES 2 & 3 HERE]

Tables 2 (panel B) and 3 (panel B) present the results from the (equal- and value-weighted, respectively) estimations of Equation (7), where we test for herding conditional upon market returns in our sample markets. To begin with, herding is significant during both up- and down-market days (reflected through significantly negative β_3 and β_4 estimates) for all tests (equal- and value-weighted ones) in most markets, with the exception of the value-weighted test for the BRVM (its β_4 estimate is insignificantly negative) and Tanzania (both β_3 and β_4 are positive). As the results indicate, there exists no concrete pattern of herding asymmetry conditional on market returns across our sample markets and within each estimation-specification (equal- versus value-weighted); when both β_3 and β_4 are

[19] Namely, estimating it using both equal- and value-weighted CSAD/$r_{m,t}$.
[20] Throughout the discussion in this section, references to statistical significance shall be taken to imply significance at the 5 percent level, unless otherwise noted.

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significantly negative, the cases where β_3 is larger in absolute terms than β_4 are the same in number with the cases where the absolute value of β_4 is larger than that of β_3.[21] Consequently, market performance does not constitute a strong determinant of herding asymmetry in African frontier markets; investors there appear to herd irrespective of market direction, with their herding in most cases being insignificantly different between up- and down- markets (for those tests where both β_3 and β_4 are significantly negative, the difference between β_3 and β_4 is found to be significant in a minority of cases[22]). A possible explanation for this is that frontier markets tend to enjoy low volumes of trade, leading to a low overall fraction of stocks actively traded every day (Speidell, 2011), thus rendering the decision to herd (indeed, trade at all) there heavily dependent on the observed (or predicted) trading activity of individual stocks rather than the (positive or negative) performance of the market as a whole. What is more, faced with the relatively low informational transparency of their markets, investors in frontier stock exchanges are expected to view herding as a viable option regardless of their market's directional movement. Another possible reason underlying our results is the relative lack of benchmarking in these markets, reflected through the absence or under-development of index-linked products (e.g. futures, options and exchange-traded funds), which further deters investors from focusing on the market's overall performance by not allowing for the implementation of trading strategies benchmarked against market indices.

Tables 2 (panel C) and 3 (panel C) present the results from Equation (8), for its equal- and value-weighted versions, respectively. As far as equal-weighted results are concerned, herding is present for most markets during both high and low volatility days (β_3 and β_4 are both significantly negative), appearing stronger during low volatility days (β_4 is larger in absolute terms than β_3); exceptions here are Kenya (its β_4 is insignificant) and Tanzania (both β_3 and β_4 are significantly negative, yet β_3 is larger in absolute terms than β_4). Turning now to value-weighted estimations, herding is present during both high and low volatility days, yet is stronger for low volatility days, for Botswana, Namibia, Nigeria and Zambia; the BRVM and Ghana exhibit herding only during low volatility days, Kenya presents us with herding during high volatility days only and Tanzania exhibits no herding

[21] $|\beta_3| > |\beta_4|$ and $|\beta_3| < |\beta_4|$ in seven cases each. See panel B in Tables 2 and 3 for more details on this.
[22] This is the case for the equal-weighted tests in Botswana, Nigeria and Tanzania and for the value-weighted tests in Ghana, Namibia and Zambia.

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whatsoever. The difference in herding between high and low volatility days is found to be significant in several cases, more so for value-weighted tests. Taken together, the above results showcase that herding exhibits considerable asymmetry conditional upon market volatility, appearing significant (or stronger, compared to high volatility days) mostly during low volatility days. The pronounced presence of significant (or stronger) herding in African frontier markets during periods characterized by low market volatility is in line with earlier literature findings from other markets (Economou et al., 2011; Holmes et al., 2013; Economou et al., 2015b) and can be attributed to several possible factors. Lower volatility allows investors easier observation of their peers' trades, thus rendering it more likely that they will herd on them; what is more, less volatile market conditions are typified by less uncertainty and provide a clearer view of the market's overall directional movement, thus facilitating herding towards the latter by investors. Less volatility may also be the result of a reduced flow of information to the market, in which case investors may well consider mimicking their peers a preferable strategy in order to free-ride on their information; this is particularly important in frontier markets, whose trading environment is characterized by reduced transparency and quality of information (Speidell, 2011).

Panels D in Tables 2 and 3 present the results from the equal- and value-weighted estimations of Equation (9) regarding the effect of the US market over our sample markets' herding. The presence of "domestic" herding (reflected through significantly negative β_2 values) matches the results from panel A of Tables 2 and 3; herding is significant for all markets, with the exception of Tanzania in its value-weighted test. The US market is found to motivate herding (as the significantly negative values of β_3 indicate) in the BRVM (equal- and value-weighted estimations), Kenya (equal-weighted estimation only) and Nigeria (equal- and value-weighted estimations). These results indicate that the US market does not motivate herding widely across African markets, something not unexpected, given the low levels of integration of these markets within the global financial system which leads them to maintain low correlations with international markets (Alagidede, 2009) and, hence, be relatively less affected by global factors compared to markets at higher stages of financial development[23].

[23] This is in stark contrast to the findings reported in Chiang and Zheng (2010), where the US market was found to motivate herding in almost all seventeen international (developed and emerging) markets of their sample.

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We now turn to the effect that the return dynamics of the South African market cast over our sample markets' herding; Panel E in Tables 2 and 3 presents the results of our equal- and value-weighted estimations of Equation (10). Results from these estimations denote a picture of "domestic" herding (reflected through significantly negative β_2 values) similar to that found in the earlier estimations of unconditional herding (panel A of Tables 2 and 3). The South African market is found to motivate herding (β_3 is significantly negative) in the BRVM (equal- and value-weighted[24] estimations), Botswana and Ghana (value-weighted estimations for both[25]). The fact that South Africa's market is found to give rise to herding in only three of our eight sample markets can be attributed to the fact that financial integration is low among African markets (Alagidede, 2009), leading investors there to be little affected in their trading behaviour by the dynamics of their continent's leading market. On the other hand, however, these findings are very interesting, as they demonstrate for the first time that herding in a continent's markets can be motivated by the return dynamics of the continent's major stock exchange; this is particularly interesting from both a research perspective (it denotes an alternative source of herding in markets internationally) as well as a regulatory one (it suggests that the dynamics of a continent's largest market can give rise to potentially destabilizing outcomes in some of the continent's other markets).

We conclude the examination of herding in African frontier markets for the full sample period by investigating the role of regional economic integration in herding formation in the context of three regional African economic initiatives, the EAC, the ECOWAS and the SACU, based on the classification of our sample's markets conducted in the previous section. Results from the equal- and value-weighted estimations of Equation (11) are shown in Table 4, panels A-C and they show that herding in a market appears rarely to be motivated by the return dynamics of other markets belonging to the same regional initiative.[26] As our results show, Ghana and Nigeria motivate herding in the BRVM (in the ECOWAS' context) and Botswana motivates herding in Namibia[27] (in the SACU's context) for the equal-weighted specification only in all three cases, thus denoting that herding in a

[24] β_3 is significantly negative for the value-weighted estimation at the 10 percent level.
[25] β_3 is significantly negative for the value-weighted estimation for both markets at the 10 percent level.
[26] As per "domestically" motivated herding (reflected through the β_2 coefficient), results are similar to those from the estimations of Equation (3) in panel A, Tables 2 and 3.
[27] The β_3 estimate is significant at the 10 percent level in this case.

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regional economic association's member-market is motivated by other member-markets' return dynamics only occasionally. A possible explanation for this is that regional economic initiatives in Africa have concentrated their focus on enhancing economic integration via the liberalization of intra-region trading, with less focus having been devoted to date on issues pertaining to financial integration, in general and stock market integration, in particular (Masson and Patillo, 2005), thus leading equity markets of member-states of these initiatives to maintain limited linkages among themselves.[28]

[PLEASE INSERT TABLE 4 HERE]

We now turn to the effect of the outbreak of the 2007-2009 global financial crisis over herding in our sample markets. Results from the equal- and value-weighted estimations of Equations (3) and (7) - (11) are presented in Tables 5-10, before (23/1/2002 – 9/10/2007), during (10/10/2007-6/3/2009) and after (7/3/2009-15/7/2015) the crisis' outbreak. Unconditional herding estimates (panel A, Tables 5–10) reveal the presence of significant herding across our eight sample markets before, during and after the crisis' outbreak for both equal- and value-weighted specifications. Herding is present in almost all equal-weighted tests (with the exception of Botswana during and after the crisis), with value-weighted tests furnishing us with more evidence of herding absence (for the BRVM and Tanzania before, during and after the crisis; for Botswana during and after the crisis; for Nigeria during the crisis; and for Ghana post crisis). Where herding in a sub period is present both for the equal- and value-weighted tests in a market, it appears stronger for the equal-weighted test (as the greater – in absolute terms – values of β_2 of those tests indicate), thus confirming that smaller stocks amplify the magnitude of herding in African frontier markets, in line with the results presented earlier in Tables 2-3.

When herding is conditioned on market returns (panel B, Tables 5-10), we notice that it, generally, demonstrates no uniform asymmetries across the three sub periods. Out of a total of 48 tests[29], herding is present exclusively during up- (down-) market days in five (two) of them. The presence of herding during both up- and down-market days (reflected through significantly negative β_3 and β_4 estimates) is

[28] The low volume of trade plaguing African frontier markets does not suffice for their proper functioning as individual stock exchanges, much less allow for cross border investment activity among them, thus rendering the lack of integration among stock exchanges at the regional level in Africa unsurprising. Other factors hindering strong regional integration among African stock markets include the lack of advanced financial technological infrastructure, the presence of capital controls in exchange movements and the under-development of their banking systems (Masson and Patillo, 2005; Speidell, 2011).

[29] We have run two tests (equal-/value-weighted) for each of the eight markets in each of the three sub-periods.

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detected in the majority (34) of tests. β_3 is larger in absolute terms than β_4 in 18 of those tests, whereas the absolute value of β_4 is larger than that of β_3 in 16 of those tests, with the distribution of these patterns varying before, during and after the crisis.[30] These results show that herding in African frontier markets exhibits no uniform asymmetry contingent upon market returns when the 2007 – 2009 crisis is used to partition the sample period, while the asymmetries detected do not appear significant in most cases; indeed, of the 34 tests where β_3 and β_4 are found to be simultaneously significantly negative, the difference between β_3 and β_4 is found to be significant for fewer than half (14) of those tests. The above indicate that market performance does not constitute a strong determinant of herding asymmetry in our sample markets before, during and after the crisis, in line with the full sample period's results. Similar to the unconditional herding estimates discussed above, we again witness that equal-weighted tests entail more evidence of herding compared to value-weighted ones across the three sub periods.

Conditioning herding on market volatility (panel C, Tables 5-10), we notice that herding is present exclusively during high (low) volatility days in 17 (3) out of a total of 48 tests, without, however, herding being significantly different from low (high) volatility days for those specific tests, except for two (two) of them.[31] The presence of herding during both high and low volatility days (reflected through significantly negative β_3 and β_4 estimates) is detected in 18 tests; β_3 (β_4) is larger in absolute terms than β_4 (β_3) in 5 (13) of those tests, with the distribution of these cases varying before, during and after the crisis.[32] Of those 18 tests where β_3 and β_4 are simultaneously significantly negative, the difference between β_3 and β_4 is found to be significant for 10 of those tests. As a general observation, equal-weighted tests are again shown to demonstrate more evidence of herding compared to value-weighted ones across the three sub periods. Taken together, these results suggest that the previously documented stronger presence of herding during low volatility days for the full sample period does not remain robust when partitioning the sample period based on the 2007-2009 crisis. It appears that

[30] Of the 18 (16) cases where β_3 is larger in absolute terms than β_4 (β_4 is larger in absolute terms than β_3), five (eight) fall into the pre crisis period, five (five) into the crisis period and eight (three) into the post crisis one.
[31] All of these four cases refer to post crisis tests.
[32] Of the 5 (13) cases where β_3 is larger in absolute terms than β_4 (β_4 is larger in absolute terms than β_3), two (six) fall into the pre crisis period, two (two) into the crisis period and one (five) into the post crisis one.

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the crisis has dislodged that pattern, which, as panel C in Tables 5-10 shows, appears mostly pre and post crisis (albeit less pronounced, compared to the full sample period's results).

[PLEASE INSERT TABLES 5 - 10 HERE]

Panel D in Tables 5-10 presents the results from the (equal- and value-weighted) estimation of Equation (9) before, during and after the crisis. The coefficient β_2 assumes values largely in line with the full sample period's results, with most evidence of herding insignificance surfacing in value-weighted estimations, especially during the crisis. The US market is found to induce herding in Ghana (pre crisis for the equal- and value-weighted tests; during the crisis for the value-weighted test[33]), Kenya (pre crisis for the equal- and value-weighted tests), Nigeria (during the crisis for the equal- and value-weighted tests[34]), the BRVM (post crisis for the equal- and value-weighted tests[35]) and Zambia (pre crisis for the equal-weighted test). The fact that the US market is found to induce herding in only 10 out of 48 tests, is perhaps hardly surprising, given the relatively low integration of African (and, in general, frontier) markets in the global financial system that allows these markets to be less affected by global factors (Alagidede, 2009).

The effect of the South African market's returns over herding in African frontier markets appears even more limited, in line with the results presented for the full sample period. Panel E, Tables 5-10[36] shows that South Africa motivates no herding in any of our sample markets pre crisis; during the crisis it is found to induce herding (β_3 is significantly negative) in Ghana (value-weighted estimation) and Nigeria (equal- and value-weighted estimations[37]), while post crisis it motivates herding in the BRVM only (equal- and value-weighted estimations[38]).

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[33] β_3 is significant at the 10 percent level.
[34] It is interesting to note that for the value-weighted test during the crisis, herding in Nigeria appears motivated only by the US market and not domestically (β_2 is insignificant, contrary to β_3 which is significantly negative).
[35] Again here for the value-weighted test after the crisis, herding in the BRVM appears motivated only by the US market and not domestically (β_2 is insignificant, contrary to β_3 which is significantly negative).
[36] With respect to "domestically" motivated herding, the coefficient β_2 assumes values largely in line with the estimations of Equation (3) in panel A, Tables 2 and 3 and panel A, Tables 5-10.
[37] For the value-weighted test during the crisis, herding in Nigeria appears motivated only by the South African market and not domestically (β_2 is insignificant, contrary to β_3 which is significantly negative).
[38] In the value-weighted test post crisis, herding in the BRVM appears motivated only by the South African market and not domestically (β_2 is significantly positive – indicative of no herding; conversely, β_3 is significantly negative). What we report in this footnote, as well as footnotes 34, 35 and 37 previously, about the role of major foreign markets in inducing herding in other markets internationally has been documented in earlier literature as well. Chiang and Zheng (2010) found that, on

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We finally turn to examine the effect of the crisis' outbreak over the role of regional economic integration in herding formation in our sample's three regional African economic initiatives. Results from panels A-C, Tables 5-10 denote that herding in a regional economic association's member-market is motivated by other member-markets' return dynamics only occasionally, in line with the full sample period's findings.[39] Most evidence in support of this emanates from equal-weighted tests during the post crisis period, where (in SACU's context) Botswana is found to motivate herding in Namibia and (in ECOWAS) Nigeria induces herding in the BRVM and Ghana[40] and Ghana causes herding in Nigeria. Regarding the rest of the sub periods, Tanzania motivates herding in Kenya pre crisis for the equal-weighted specification[41] and Ghana induces herding in Nigeria during the crisis (value-weighted specification[42]).

4. Conclusion

Frontier markets constitute a category of markets for which little is known about the tendency of their investors to herd, unlike for developed and emerging markets, for which research is prolific. Our study contributes to research on this issue by investigating herding in a sample of eight African frontier markets for the 2002-2015 period. Herding is present across all eight markets and we attribute this to the low transparency levels prevalent in frontier stock exchanges that reduce the quality of their informational environment, thus leading investors there to deem herding a feasible option, allowing them to infer information from their peers' trades. Interestingly enough, the magnitude of herding grows larger when herding is estimated based on equal- (compared to value-) weighted tests, which suggests that smaller capitalization stocks amplify its size; this is not surprising, given the greater informational uncertainty surrounding smaller stocks, leading investors to herd more when trading them. Herding is not found to exhibit significant asymmetries conditional on different market states; this is the case, particularly, with market returns, where herding appears significant irrespective of the

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several occasions, the US market motivated herding in international markets, without these markets bearing any "domestically" motivated herding.

[39] As per "domestically" motivated herding (reflected through the β_2 coefficient), results are similar to those from the estimations of Equation (3) in panel A, Tables 2 and 3 and panel A, Tables 5-10.

[40] β_3 is significant at the 10 percent level for both cases.

[41] β_3 is significant at the 10 percent level.

[42] β_3 is significant at the 10 percent level.

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market's directional movement in most cases. On the other hand, herding does exhibit asymmetric behaviour with respect to market volatility, as it appears significant (or stronger, compared to high volatility days) mainly during days of low volatility; however, this pattern grows weak when partitioning our sample period to account for the 2007-2009 global financial crisis. Although "domestically" motivated herding is significant across all eight markets, the same cannot be argued for herding induced by the US and South African market returns, the presence of which is confirmed on only a small number of occasions; similarly, the return dynamics of a regional economic initiative's member-markets are found to motivate herding in each other very rarely. These results are very interesting, as they indicate that investors' behaviour in African frontier markets is not significantly affected by non-domestic factors and are in line with extant research denoting the overall low levels of integration of frontier markets within the global financial system.

Our findings are of particular interest to investors, primarily those with an international outlook, as the presence of significant herding documented in this study suggests that herding can be utilized as input to inform their equity trading strategies in frontier markets, in general, and African frontier markets, in particular, considering the widely documented diversification benefits accruing from investing in frontier markets. From a research perspective, the fact that South Africa is found to motivate herding in some of our sample markets indicates for the first time in the literature that a continent's lead market is a herding determinant for some of the continent's other markets, thus denoting an alternative source of herding that needs to be taken into account in future research. Furthermore, the fact that the dynamics of the US and South Africa can induce herding in some of Africa's frontier markets is of key importance to regulators and policymakers in these markets, since it suggests that these dynamics can give rise to potentially destabilizing outcomes and should, thus, be more closely monitored. What is more, the significant herding documented in African frontier markets suggests that regulatory measures aiming at containing it (by enhancing e.g., transparency and investors' trust) are necessary in order to prevent the occurrence of destabilizing outcomes as a result of it. Any such measures aiming at improving the quality of the informational environment will further render these markets more attractive to international investors and increase their volume levels, something vital for

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the viability of these markets and their progression along the evolutionary trajectory towards the emerging markets' stage.

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Table 1: Descriptive statistics

Panel A: Descriptive statistics on the equal- and value-weighted versions of $CSAD_{m,t}$ and $r_{m,t}$

	$r_{m,t}$				$CSAD_{m,t}$			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Botswana	0.0607	0.4386	0.0582	0.4744	0.5231	0.6574	0.5242	0.6079
BRVM	0.0305	0.4237	0.0397	0.5048	0.6885	0.4530	0.8358	0.6162
Ghana	0.0587	0.7536	0.0501	3.4869	0.6773	0.5747	2.0622	1.6171
Kenya	0.0537	0.6629	0.0867	0.8843	1.3685	0.4668	1.4452	0.4978
Namibia	0.0366	0.7379	0.0410	1.3184	0.9760	0.5233	1.1764	0.6432
Nigeria	0.0128	0.5259	0.0647	1.0409	1.3839	0.5880	1.6230	0.6619
Tanzania	0.0865	0.6433	0.1120	0.6569	0.7328	0.5992	0.0083	0.0067
Zambia	0.0845	0.8067	0.0643	1.0984	1.1246	0.9679	0.9974	0.9388

Panel B: Ljung-Box test statistics (10 lags) on the equal- and value-weighted versions of $r_{m,t}$

	Equal-weighted $r_{m,t}$		Value-weighted $r_{m,t}$	
	LB statistic	p-value	LB-statistic	p-value
Botswana	100.332	0.0000	463.538	0.0000
BRVM	179.053	0.0000	105.524	0.0000
Ghana	256.179	0.0000	89.741	0.0000
Kenya	1435.151	0.0000	924.187	0.0000
Namibia	42.283	0.0000	25.982	0.0038
Nigeria	3231.561	0.0000	1014.759	0.0000
Tanzania	71.454	0.0000	146.546	0.0000
Zambia	62.455	0.0000	44.915	0.0000

Panel C: Correlations between each of the sample markets and the US and South Africa; equal-weighted market returns for our eight sample markets (full sample period)

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
S&P 500	0.0080	0.0116	0.0558	-0.0001	0.2772	-0.0008	0.0594	0.0143
FTSE/JSE All Shares	0.0021	0.0138	0.0819	0.0090	0.6365	0.0214	-0.0097	0.0144

Panel D: Correlations between each of the sample markets and the US and South Africa; value-weighted market returns for our eight sample markets (full sample period)

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
S&P 500	0.0165	0.0080	0.1154	0.0122	0.1824	-0.0036	0.0354	0.0118
FTSE/JSE All Shares	-0.0120	-0.0183	0.3310	-0.0002	0.4761	0.0321	0.0093	-0.0397

Panel E: Correlations between each of the sample markets and the US and South Africa; equal-weighted market returns for our eight sample markets (crisis period: 10/10/2007-6/3/2009)

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
S&P 500	-0.0145	0.0283	0.1418	-0.0018	0.2686	0.0034	0.0384	0.0139
FTSE/JSE All Shares	0.0031	0.0374	0.2812	0.0704	0.6518	0.0135	0.0017	-0.0146

Panel F: Correlations between each of the sample markets and the US and South Africa; value-weighted market returns for our eight sample markets (crisis period: 10/10/2007-6/3/2009)

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
S&P 500	-0.0005	0.0773	0.1635	0.0571	0.1750	-0.0048	0.0552	-0.0394
FTSE/JSE All Shares	-0.0483	-0.0262	0.4710	0.0852	0.4992	0.0063	0.0189	-0.1051

Panel A presents descriptive statistics (mean and standard deviation) of the equal- and value-weighted versions of the market return ($r_{m,t}$) and cross sectional absolute deviation ($CSAD_{m,t}$) for all eight sample markets for the January 23rd, 2002 – July 15th, 2015 period. Panel B presents Ljung-Box test-statistics for the equal- and value-weighted versions of the market return ($r_{m,t}$) for all eight sample markets for ten (10) lags. Panels C to F present correlation coefficients between each of our sample's eight markets (equal- and value-weighted market returns) and the US (S&P500) and South Africa (FTSE/JSE All Share) for the full sample period and for the crisis period only (10/10/2007 – 6/3/2009).

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Table 2: Full sample period equal-weighted herding estimates for our sample markets

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
Panel A: Unconditional herding estimations								
β_0	0.0606	0.3004	0.3642	0.9986	0.5187	0.8847	0.1373	0.1539
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.9223	1.7451	0.9840	0.9770	1.0806	1.6655	1.6850	2.1293
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1221	-0.3918	-0.1390	-0.1534	-0.1477	-0.4088	-0.2792	-0.3001
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
R^2_{adj}	0.8783	0.6197	0.3931	0.4714	0.5922	0.4972	0.7969	0.8274
Panel B: Herding estimations conditional on market returns								
β_0	0.0612	0.3005	0.3641	1.0005	0.5182	0.8895	0.1351	0.1531
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.8195	1.7631	0.9646	1.0106	1.100	1.8244	1.6563	2.0960
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	2.0755	1.7231	1.0101	0.9187	1.0598	1.4645	1.7509	2.1799
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0865	-0.3924	-0.1345	-0.1630	-0.1523	-0.5067	-0.2664	-0.2893
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_4	-0.1669	-0.3932	-0.1453	-0.1318	-0.1426	-0.2880	-0.3076	-0.3172
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	53.9975	1.1405	1.7893	7.0874	2.0150	31.8326	6.2063	3.1212
	(0.0000)***	(0.2856)	(0.1811)	(0.0078)***	(0.1559)	(0.0000)***	(0.0128)**	(0.0774)*
F_2 (H_0: $\beta_3 = \beta_4$)	19.3731	0.0019	2.0469	2.6275	0.6137	17.6421	4.9884	1.3349
	(0.0000)***	(0.9648)	(0.1526)	(0.1051)	(0.4335)	(0.0000)***	(0.0256)**	(0.2481)
R^2_{adj}	0.8809	0.6198	0.3932	0.4724	0.5923	0.5025	0.7973	0.8275
Panel C: Herding estimations conditional on market volatility								
β_0	0.0466	0.2894	0.3317	0.9803	0.4929	0.8103	0.1457	0.1502
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.9107	1.7372	1.0287	0.9322	1.0585	1.4787	1.6855	2.1276
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	2.1107	1.8656	1.2889	1.0684	1.2298	2.4239	1.6241	2.1554
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.1150	-0.3855	-0.1433	-0.1367	-0.1393	-0.2682	-0.2800	-0.2985
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_4	-0.2500	-0.4904	-0.4550	-0.0693	-0.1697	-0.8677	-0.2743	-0.3149
	(0.0000)***	(0.0000)***	(0.0000)***	(0.3590)	(0.0002)***	(0.0000)***	(0.0000)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	14.2983	7.8452	18.2344	4.7965	12.4383	117.6481	1.4722	0.2223
	(0.0002)***	(0.0051)***	(0.0000)***	(0.0286)**	(0.0004)***	(0.0000)***	(0.2251)	(0.6374)
F_2 (H_0: $\beta_3 = \beta_4$)	5.4141	7.2309	68.0960	0.8424	0.4848	31.1592	0.0256	0.1283
	(0.0200)**	(0.0072)***	(0.0000)***	(0.3588)	(0.4863)	(0.0000)***	(0.8728)	(0.7202)
R^2_{adj}	0.8789	0.6205	0.4080	0.4791	0.5972	0.5291	0.7970	0.8273
Panel D: Herding estimations controlling for the effect of US market returns								
β_0	0.0598	0.3042	0.3641	0.9859	0.5095	0.8892	0.1396	0.1532
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.9221	1.7455	0.9840	0.9927	1.0765	1.6622	1.6839	2.1295
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1220	-0.3919	-0.1390	-0.1556	-0.1564	-0.4024	-0.2788	-0.3002
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	0.0005	-0.0025	0.0001	-0.0022	0.0109	-0.0033	-0.0013	0.0004
	(0.5011)	(0.0069)***	(0.9713)	(0.0485)***	(0.0000)***	(0.0202)***	(0.1979)	(0.7993)
R^2_{adj}	0.8783	0.6204	0.3930	0.4845	0.6014	0.4979	0.7970	0.8273
Panel E: Herding estimations controlling for the effect of South African market returns								
β_0	0.0602	0.3057	0.3604	1.0033	0.5188	0.8816	0.1554	0.1532
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.9245	1.7443	0.9781	0.9716	1.0630	1.6678	1.5930	2.1318
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1235	-0.3907	-0.1373	-0.1521	-0.1488	-0.4132	-0.2318	-0.3004
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	0.0003	-0.0040	0.0035	-0.0004	0.0067	0.0023	0.0077	-0.0005
	(0.7863)	(0.0068)***	(0.1163)	(0.7927)	(0.0008)***	(0.2979)	(0.0263)**	(0.8412)
R^2_{adj}	0.8754	0.6203	0.3931	0.4693	0.5930	0.4956	0.7580	0.8274

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP})r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH})r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the full sample period (23/1/2002 – 15/7/2015). CSAD refers to the equal-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the equal-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 3: Full sample period value-weighted herding estimates for our sample markets

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
Panel A: Unconditional herding estimations								
β_0	0.2005	0.3348	0.5208	1.0553	0.06473	1.0315	0.0035	0.5533
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.3291	1.5695	0.8246	0.7733	0.6874	0.8862	0.0089	1.3973
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.0575	-0.1764	-0.0203	-0.0870	-0.0387	-0.0752	0.0014	-0.1186
	(0.0000)***	(0.0013)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0023)***	(0.0000)***
R^2_{adj}	0.6202	0.6828	0.7926	0.4790	0.6069	0.5489	0.5825	0.5998
Panel B: Herding estimations conditional on market returns								
β_0	0.2011	0.3367	0.5021	1.0541	0.6303	1.0324	0.0037	0.5516
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.3121	1.5647	0.8465	0.7866	0.7755	0.9085	0.0070	1.3737
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.3417	1.5266	0.8312	0.7652	0.6780	0.8577	0.0078	1.4473
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0597	-0.1883	-0.0235	-0.0880	-0.0642	-0.0838	0.0022	-0.1131
	(0.0000)***	(0.0032)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0001)***	(0.0000)***
β_4	-0.0441	-0.1062	-0.0191	-0.0892	-0.0368	-0.0646	0.0033	-0.1294
	(0.0133)**	(0.2142)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0013)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	0.3325	0.1887	1.8635	0.6355	26.4540	2.1688	0.4437	2.2338
	(0.5642)	(0.6641)	(0.1723)	(0.4254)	(0.0000)***	(0.1409)	(0.5054)	(0.1352)
F_2 (H_0: $\beta_3 = \beta_4$)	0.5982	0.7446	46.2050	0.0124	28.6173	1.5889	1.1946	5.1976
	(0.4393)	(0.3883)	(0.0000)***	(0.9115)	(0.0000)***	(0.2076)	(0.2745)	(0.0227)**
R^2_{adj}	0.6206	0.6828	0.7975	0.4791	0.6105	0.5489	0.5887	0.6006
Panel C: Herding estimations conditional on market volatility								
β_0	0.1596	0.6150	0.5207	1.0482	0.5994	0.9929	0.0031	0.5244
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.3328	1.3513	0.7656	0.7440	0.6899	0.8459	0.0078	1.3628
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.9105	1.9302	0.8253	0.7752	0.8648	1.0433	0.0127	1.7139
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0542	0.1173	0.0009	-0.0801	-0.0381	-0.0571	0.0023	-0.1136
	(0.0000)***	(0.1924)	(0.9560)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_4	-0.5957	-0.7588	-0.0205	-0.0035	-0.0911	-0.1056	-0.0013	-0.2208
	(0.0000)***	(0.0000)***	(0.0000)***	(0.9332)	(0.0000)***	(0.0000)***	(0.1706)	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	35.7295	29.9085	0.8303	0.4292	20.3906	11.9938	23.3310	28.6875
	(0.0000)***	(0.0000)***	(0.3623)	(0.5124)	(0.0000)***	(0.0005)***	(0.0000)***	(0.0000)***
F_2 (H_0: $\beta_3 = \beta_4$)	16.1161	62.4449	1.7486	3.4878	4.7188	1.1453	13.7849	21.3480
	(0.0001)***	(0.0000)***	(0.1861)	(0.0619)*	(0.0299)**	(0.2846)	(0.0002)***	(0.0000)***
R^2_{adj}	0.6252	0.6944	0.7927	0.4834	0.6115	0.5532	0.5877	0.6047
Panel D: Herding estimations controlling for the effect of US market returns								
β_0	0.2006	0.3385	0.5236	1.0427	0.6324	1.0369	0.0035	0.5504
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.3292	1.5683	0.8261	0.7823	0.6758	0.8860	0.0089	1.3964
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.0575	-0.1759	-0.0203	-0.0878	-0.0384	-0.0740	0.0014	-0.1185
	(0.0000)***	(0.0014)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0024)***	(0.0000)***
β_3	-0.0001	-0.0023	-0.0036	-0.0011	0.0166	-0.0043	-0.000003	0.0019
	(0.9554)	(0.0519)*	(0.1359)	(0.3699)	(0.0000)***	(0.0049)**	(0.8439)	(0.4390)
R^2_{adj}	0.6201	0.6830	0.7927	0.4905	0.6224	0.5499	0.5823	0.5997
Panel E: Herding estimations controlling for the effect of South African market returns								
β_0	0.2046	0.3378	0.4367	1.0614	0.6427	1.0269	0.0035	0.5414
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.3324	1.5674	0.8973	0.7667	0.6634	0.8874	0.0069	1.3897
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.0582	-0.1683	-0.0259	-0.0855	-0.0374	-0.0754	0.0026	-0.1179
	(0.0000)***	(0.0024)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0004)***	(0.0000)***
β_3	-0.0035	-0.0032	-0.0064	-0.0004	0.0164	0.0028	0.00003	0.0087
	(0.0830)*	(0.0807)*	(0.0779)*	(0.8134)	(0.0000)***	(0.2342)	(0.5612)	(0.0147)**
R^2_{adj}	0.6285	0.6862	0.8145	0.4748	0.6131	0.5495	0.6627	0.6011

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP}) r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH}) r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the full sample period (23/1/2002 – 15/7/2015). CSAD refers to the value-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the value-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 4: The effect of regional economic integration over herding estimates

Panel A: East African Community

Effect of Tanzania's market returns over Kenya's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	1.0516	0.9352	1.0677	1.0999	β_0	1.0865	0.9936	1.1493	1.1421
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	0.9136	1.2416	0.7254	0.7309	β_1	0.7514	0.9955	0.5721	0.5859
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1435	-0.2276	-0.0889	-0.0839	β_2	-0.0887	-0.1403	-0.0512	-0.0429
	(0.0000)***	(0.0000)***	(0.0108)**	(0.0001)***		(0.0000)***	(0.0000)***	(0.0058)***	(0.0360)**
β_3	0.0001	-0.0167	0.0105	0.0715	β_3	0.0201	-0.0089	0.0147	0.0434
	(0.9875)	(0.0508)*	(0.6821)	(0.0000)***		(0.0665)*	(0.6839)	(0.6393)	(0.0008)***
R^2_{adj}	0.4299	0.4851	0.5763	0.3582	R^2_{adj}	0.4608	0.5258	0.5561	0.3584

Effect of Kenya's market returns over Tanzania's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.1379	0.2131	0.0699	0.1050	β_0	0.0034	0.0051	0.0025	0.0024
	(0.0000)***	(0.0000)***	(0.0181)**	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.6881	1.4128	1.7034	1.8997	β_1	0.0091	0.0079	0.0084	0.0111
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.2799	-0.2049	-0.2428	-0.3438	β_2	0.0013	0.0008	0.0028	0.0008
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0042)***	(0.4482)	(0.0117)**	(0.1110)
β_3	-0.0010	0.0026	0.0159	-0.0137	β_3	0.0001	0.00001	0.0001	-0.0001
	(0.8450)	(0.7425)	(0.0000)***	(0.1753)		(0.2953)	(0.9578)	(0.0803)*	(0.4504)
R^2_{adj}	0.7991	0.7459	0.8919	0.8267	R^2_{adj}	0.5906	0.3934	0.7423	0.7268

Panel B: Southern African Customs Union

Effect of Namibia's market returns over Botswana's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.0608	0.0709	0.0728	0.0682	β_0	0.1841	0.2606	0.1984	0.1439
	(0.0000)***	(0.0000)***	(0.0001)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.9320	1.9359	1.7404	1.7832	β_1	1.3432	1.4868	1.0111	1.3108
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1280	-0.1368	0.0292	0.0312	β_2	-0.0654	-0.1042	0.0282	-0.0889
	(0.0000)***	(0.0000)***	(0.5912)	(0.2568)		(0.0000)***	(0.0000)***	(0.1169)	(0.0063)***
β_3	-0.0007	0.0064	-0.0019	0.0001	β_3	0.0063	0.0083	-0.0030	-0.0024
	(0.8157)	(0.5179)	(0.4746)	(0.9865)		(0.0000)***	(0.0001)***	(0.2349)	(0.3171)
R^2_{adj}	0.8693	0.8483	0.8848	0.8866	R^2_{adj}	0.6204	0.5799	0.8353	0.6478

Effect of Botswana's market returns over Namibia's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.5438	0.4380	1.0102	0.5823	β_0	0.6538	0.5757	1.1435	0.6318
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.0582	1.0946	0.7455	0.9962	β_1	0.7109	0.7339	0.5855	0.7348
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1423	-0.1423	-0.0992	-0.1218	β_2	-0.0475	-0.0463	-0.0522	-0.0578
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0167	0.0037	0.0049	-0.1097	β_3	0.0029	0.0034	0.0071	-0.0403
	(0.0560)*	(0.6414)	(0.9411)	(0.0014)***		(0.6685)	(0.6599)	(0.6998)	(0.1134)
R^2_{adj}	0.5752	0.6590	0.4624	0.5094	R^2_{adj}	0.5890	0.6592	0.4525	0.5574

Panel C: Economic Community of West African States

Effect of Ghana's market returns over BRVM's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.3239	0.1298	0.2661	0.4806	β_0	0.3420	0.2423	0.3354	0.5309
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.7219	1.8962	1.8182	1.5485	β_1	1.5187	1.5324	1.2223	0.9606
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.3883	-0.4110	-0.4293	-0.4189	β_2	-0.1380	-0.1014	0.1826	0.2294
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0162)**	(0.3443)	(0.3702)	(0.0000)***
β_3	-0.0036	0.0004	-0.0220	-0.0026	β_3	0.0001	0.0003	0.0017	-0.0002
	(0.0202)**	(0.6730)	(0.5815)	(0.7926)		(0.1894)	(0.1151)	(0.0001)***	(0.1537)
R^2_{adj}	0.5987	0.8229	0.7178	0.4812	R^2_{adj}	0.6869	0.6921	0.6861	0.6488

Effect of Nigeria's market returns over BRVM's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.3282	0.1321	0.2754	0.4862	β_0	0.3428	0.2407	0.3817	0.5272
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.7276	1.8968	1.8153	1.5444	β_1	1.5169	1.5359	1.2273	0.9644
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.3898	-0.4113	-0.4294	-0.4132	β_2	-0.1347	-0.0979	0.1804	0.2241
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0188)**	(0.3615)	(0.3884)	(0.0025)***
β_3	-0.0278	-0.0096	-0.0125	-0.0319	β_3	0.0005	0.0033	-0.0080	0.0017
	(0.0027)***	(0.5178)	(0.3511)	(0.0734)*		(0.8631)	(0.5788)	(0.4048)	(0.6560)
R^2_{adj}	0.5992	0.8229	0.7183	0.4823	R^2_{adj}	0.6867	0.6914	0.6705	0.6484

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Table 4 (continued)

Effect of BRVM's market returns over Ghana's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.3563	0.2741	0.0584	0.2652	β_0	0.5042	0.2462	0.2341	0.7094
	(0.0000)***	(0.0000)***	(0.0017)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.0473	0.6277	2.1156	2.0593	β_1	0.8188	0.7897	1.0166	0.8397
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1420	-0.0815	-0.4269	-0.5073	β_2	-0.0199	-0.0212	-0.0364	-0.0174
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0008	0.0139	-0.0077	0.0277	β_3	0.1401	0.1794	-0.0024	-0.0253
	(0.9342)	(0.2656)	(0.3648)	(0.3079)		(0.0000)***	(0.0066)***	(0.9663)	(0.4951)
R^2_{adj}	0.4350	0.2803	0.8698	0.7598	R^2_{adj}	0.7965	0.7366	0.9431	0.8529

Effect of Nigeria's market returns over Ghana's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.3613	0.2762	0.0388	0.2748	β_0	0.5333	0.2530	0.2441	0.6942
	(0.0000)***	(0.0000)***	(0.0530)*	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.0460	0.6274	2.1099	2.0589	β_1	0.8195	0.7910	1.0174	0.8391
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1419	0.0816	-0.4213	-0.5078	β_2	-0.0199	-0.0211	-0.0364	-0.0174
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0173	0.0055	0.0191	-0.0313	β_3	0.0069	0.0224	-0.0091	0.0083
	(0.2206)	(0.8812)	(0.0375)**	(0.0736)*		(0.3107)	(0.1036)	(0.3990)	(0.2512)
R^2_{adj}	0.4354	0.2794	0.8714	0.7601	R^2_{adj}	0.7953	0.7354	0.9432	0.8529

Effect of BRVM's market returns over Nigeria's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.8708	1.1018	1.5098	0.7510	β_0	1.0126	1.1583	1.8732	0.7921
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.6725	1.3537	1.1283	1.4237	β_1	0.8618	0.7714	0.3857	0.9229
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0043)***	(0.0000)***
β_2	-0.4143	-0.2707	-0.3319	-0.1897	β_2	-0.0681	-0.0420	-0.0264	-0.0631
	(0.0000)***	(0.0016)***	(0.0007)***	(0.0000)***		(0.0000)***	(0.0234)**	(0.5541)	(0.0000)***
β_3	0.0294	0.0191	-0.0028	-0.0044	β_3	0.0865	0.2820	-0.0503	0.0672
	(0.0000)***	(0.0878)*	(0.9153)	(0.8749)		(0.0000)***	(0.0000)***	(0.5001)	(0.0003)***
R^2_{adj}	0.4982	0.3759	0.2195	0.6224	R^2_{adj}	0.5396	0.5508	0.1477	0.7669

Effect of Ghana's market returns over Nigeria's herding

Equal-weighted	Full period	Pre crisis	Crisis	Post crisis	Value-weighted	Full period	Pre crisis	Crisis	Post crisis
β_0	0.8740	1.1075	1.5254	0.7571	β_0	1.0344	1.2161	1.8710	0.8076
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.6794	1.3576	1.1375	1.4244	β_1	0.8600	0.7572	0.3914	0.9257
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		(0.0000)***	(0.0000)***	(0.0035)***	(0.0000)***
β_2	-0.4179	-0.2746	-0.3384	-0.1917	β_2	-0.0674	-0.0400	-0.0246	-0.0638
	(0.0000)***	(0.0014)***	(0.0005)***	(0.0000)***		(0.0000)***	(0.0372)***	(0.5802)	(0.0000)***
β_3	0.0009	-0.0019	-0.1156	-0.0230	β_3	0.0002	0.0001	-0.0012	0.0004
	(0.6942)	(0.4030)	(0.1707)	(0.0187)**		(0.1153)	(0.5452)	(0.0616)*	(0.0012)***
R^2_{adj}	0.4965	0.3745	0.2245	0.6238	R^2_{adj}	0.5370	0.5193	0.1565	0.7665

The table presents the (equal- and value-weighted) estimates from the following equations:

Panel A:

$CSAD_{KENYA,t} = \beta_0 + \beta_1|r_{KENYA,t}| + \beta_2 r^2_{KENYA,t} + \beta_3 r^2_{TANZANIA,t} + \varepsilon_t$ (Effect of Tanzania's market returns over Kenya's herding)

$CSAD_{TANZANIA,t} = \beta_0 + \beta_1|r_{TANZANIA,t}| + \beta_2 r^2_{TANZANIA,t} + \beta_3 r^2_{KENYA,t} + \varepsilon_t$ (Effect of Kenya's market returns over Tanzania's herding)

Panel B:

$CSAD_{BOTSWANA,t} = \beta_0 + \beta_1|r_{BOTSWANA,t}| + \beta_2 r^2_{BOTSWANA,t} + \beta_3 r^2_{NAMIBIA,t} + \varepsilon_t$ (Effect of Namibia's market returns over Botswana's herding)

$CSAD_{NAMIBIA,t} = \beta_0 + \beta_1|r_{NAMIBIA,t}| + \beta_2 r^2_{NAMIBIA,t} + \beta_3 r^2_{BOTSWANA,t} + \varepsilon_t$ (Effect of Botswana's market returns over Namibia's herding)

Panel C:

$CSAD_{BRVM,t} = \beta_0 + \beta_1|r_{BRVM,t}| + \beta_2 r^2_{BRVM,t} + \beta_3 r^2_{GHANA,t} + \varepsilon_t$ (Effect of Ghana's market returns over BRVM's herding)

$CSAD_{BRVM,t} = \beta_0 + \beta_1|r_{BRVM,t}| + \beta_2 r^2_{BRVM,t} + \beta_3 r^2_{NIGERIA,t} + \varepsilon_t$ (Effect of Nigeria's market returns over BRVM's herding)

$CSAD_{GHANA,t} = \beta_0 + \beta_1|r_{GHANA,t}| + \beta_2 r^2_{GHANA,t} + \beta_3 r^2_{BRVM,t} + \varepsilon_t$ (Effect of BRVM's market returns over Ghana's herding)

$CSAD_{GHANA,t} = \beta_0 + \beta_1|r_{GHANA,t}| + \beta_2 r^2_{GHANA,t} + \beta_3 r^2_{NIGERIA,t} + \varepsilon_t$ (Effect of Nigeria's market returns over Ghana's herding)

$CSAD_{NIGERIA,t} = \beta_0 + \beta_1|r_{NIGERIA,t}| + \beta_2 r^2_{NIGERIA,t} + \beta_3 r^2_{BRVM,t} + \varepsilon_t$ (Effect of BRVM's market returns over Nigeria's herding)

$CSAD_{NIGERIA,t} = \beta_0 + \beta_1|r_{NIGERIA,t}| + \beta_2 r^2_{NIGERIA,t} + \beta_3 r^2_{GHANA,t} + \varepsilon_t$ (Effect of Ghana's market returns over Nigeria's herding)

All estimations involve Newey-West consistent estimators and pertain to the full sample period (23/1/2002 – 15/7/2015), pre, during and post crisis. CSAD refers to the cross sectional absolute deviation of returns, calculated both equal- and value-weighted; $r_{m,t}$ is the average market return, calculated both equal- and value-weighted; the subscripts in the equations denote the respective sample markets. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 5: Pre crisis period (23/1/2002 – 9/10/2007) equal-weighted herding estimates for our sample markets

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
Panel A: Unconditional herding estimations								
β_0	0.0743	0.1302	0.2952	0.8864	0.4195	1.0751	0.2158	0.0327
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.2430)
β_1	1.9259	1.8767	0.5599	1.2739	1.1260	1.3641	1.4091	2.2073
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1319	-0.4047	-0.0758	-0.2369	-0.1521	-0.2515	-0.2040	-0.3092
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
R^2_{adj}	0.8571	0.8335	0.2319	0.5111	0.6816	0.4057	0.7411	0.8889
Panel B: Herding estimations conditional on market returns								
β_0	0.7050	0.1302	0.2954	0.8857	0.4196	1.0902	0.2130	0.0303
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.2799)
β_1	1.8145	1.8974	0.6325	1.2900	1.1195	1.3998	1.3627	2.1598
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	2.1581	1.8512	0.4381	1.2599	1.1319	1.0530	1.4905	2.3214
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0998	-0.4061	-0.0842	-0.2399	-0.1472	-0.3017	-0.1896	-0.2883
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0001)***	(0.0000)***	(0.0000)***
β_4	-0.1937	-0.4035	-0.0618	-0.2398	-0.1560	0.1396	-0.2321	-0.3597
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.4081)	(0.0000)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	28.0721	1.4715	16.0293	0.2199	0.0752	7.0364	3.8486	4.2463
	(0.0000)***	(0.2253)	(0.0001)***	(0.6392)	(0.7840)	(0.0081)***	(0.0502)*	(0.0397)**
F_2 (H_0: $\beta_3 = \beta_4$)	9.9328	0.0261	5.9304	0.000002	0.1245	7.1870	2.4508	3.4540
	(0.0017)***	(0.8717)	(0.0150)**	(0.0000)***	(0.7243)	(0.0074)***	(0.1180)	(0.0635)*
R^2_{adj}	0.8615	0.8337	0.2427	0.5107	0.6812	0.4082	0.7420	0.8893
Panel C: Herding estimations conditional on market volatility								
β_0	0.0461	0.1175	0.2475	0.8254	0.4271	1.0353	0.2445	0.0585
	(0.0133)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.1146)
β_1	1.9194	1.8612	0.5823	1.1991	1.1173	1.1789	1.4013	2.2016
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	2.1839	2.0176	0.9842	1.6798	1.0578	1.7051	1.2415	2.0633
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.1249	-0.3961	-0.0771	-0.2029	-0.1510	-0.1015	-0.2044	-0.3116
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.1975)	(0.0000)***	(0.0000)***
β_4	-0.3079	-0.5041	-0.3206	-0.3736	-0.0707	-0.2802	-0.1562	-0.2332
	(0.0016)***	(0.0000)***	(0.0000)***	(0.0032)***	(0.3259)	(0.2467)	(0.0033)***	(0.1233)
F_1 (H_0: $\beta_1 = \beta_2$)	7.1884	11.9893	20.2845	19.9008	0.7545	11.3004	3.2440	0.9877
	(0.0075)***	(0.0006)***	(0.0000)***	(0.0000)***	(0.3852)	(0.0008)***	(0.0722)*	(0.3207)
F_2 (H_0: $\beta_3 = \beta_4$)	3.6863	13.8382	26.8957	1.9295	1.3137	0.5994	0.9304	0.2930
	(0.0551)*	(0.0002)***	(0.0000)***	(0.1650)	(0.2519)	(0.4389)	(0.3351)	(0.5885)
R^2_{adj}	0.8579	0.8352	0.2477	0.5322	0.6815	0.4210	0.7420	0.8889
Panel D: Herding estimations controlling for the effect of US market returns								
β_0	0.0654	0.1313	0.3149	0.9098	0.4115	1.0798	0.2145	0.0431
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.1302)
β_1	1.9224	1.8764	0.5795	1.2619	1.1219	1.3659	1.4063	2.2072
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1316	-0.4047	-0.0765	-0.2337	-0.1550	-0.2542	-0.2036	-0.3067
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0006)***	(0.0000)***	(0.0000)***
β_3	0.0102	-0.0010	-0.0329	-0.0195	0.0116	-0.0048	0.0028	-0.0143
	(0.0269)**	(0.6284)	(0.0000)***	(0.0000)***	(0.0009)***	(0.3339)	(0.6128)	(0.0552)*
R^2_{adj}	0.8576	0.8334	0.2476	0.5168	0.6840	0.4057	0.7408	0.8894
Panel E: Herding estimations controlling for the effect of South African market returns								
β_0	0.0758	0.1278	0.2865	0.8902	0.4195	1.0737	0.2672	0.0438
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.1448)
β_1	1.9305	1.8831	0.5570	1.2752	1.1118	1.3729	1.3071	2.2084
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1352	-0.4054	-0.0749	-0.2374	-0.1501	-0.2570	-0.1724	-0.3098
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0006)***	(0.0000)***	(0.0000)***
β_3	0.0011	0.0007	0.0072	-0.0019	0.0045	0.0003	0.0073	-0.0079
	(0.8017)	(0.7116)	(0.1648)	(0.6414)	(0.1695)	(0.9415)	(0.4332)	(0.1946)
R^2_{adj}	0.8520	0.8331	0.2346	0.5096	0.6817	0.4068	0.6128	0.8880

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP}) r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH}) r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the pre crisis period (23/1/2002 – 9/10/2007). CSAD refers to the equal-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the equal-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 6: Pre crisis period (23/1/2002 – 9/10/2007) value-weighted herding estimates for our sample markets

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
Panel A: Unconditional herding estimations								
β_0	0.2899	0.2621	0.2922	0.9529	0.5678	1.1642	0.0052	0.5466
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.4658	1.5877	0.7723	1.0091	0.7117	0.8167	0.0076	1.4044
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1048	-0.1601	-0.0200	-0.1416	-0.0386	-0.0533	0.0008	-0.1140
	(0.0000)***	(0.1219)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0005)***	(0.4460)	(0.0000)***
R^2_{adj}	0.5542	0.6490	0.7270	0.5156	0.6792	0.5627	0.3785	0.6113
Panel B: Herding estimations conditional on market returns								
β_0	0.2887	0.2655	0.2908	0.9502	0.5496	1.1633	0.0051	0.5366
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.3699	1.6558	0.7639	1.0107	0.7955	0.8154	0.0055	1.3899
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0023)***	(0.0000)***
β_2	1.6911	1.3609	0.7859	1.0318	0.7085	0.8224	0.0117	1.5112
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0871	-0.2545	-0.0192	-0.1393	-0.0635	-0.0576	0.0021	-0.1078
	(0.0000)***	(0.0378)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0014)***	(0.0626)*	(0.0000)***
β_4	-0.1126	0.1385	-0.0210	-0.1560	-0.0379	-0.0467	-0.0025	-0.1408
	(0.0227)**	(0.4166)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0250)**	(0.2959)	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	7.6102	2.5446	1.0019	0.1656	9.4276	0.0191	5.5478	2.1907
	(0.0059)***	(0.1109)	(0.3170)	(0.6841)	(0.0022)***	(0.9000)	(0.0188)**	(0.1393)
F_2 (H_0: $\beta_3 = \beta_4$)	0.2509	4.0755	2.7296	0.5997	9.5219	0.2127	3.7281	6.5322
	(0.0000)***	(0.0437)**	(0.0988)*	(0.4388)	(0.0021)***	(0.6447)	(0.0540)*	(0.0108)**
R^2_{adj}	0.6166	0.6499	0.7273	0.5152	0.6812	0.5626	0.3836	0.6151
Panel C: Herding estimations conditional on market volatility								
β_0	0.2500	0.2572	0.2927	0.9208	0.5431	1.1059	0.0045	0.5449
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.5018	2.1425	0.7710	0.9491	0.7119	0.8153	0.0052	1.4019
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.9865	1.6508	0.7679	1.1372	0.7841	1.1162	0.0155	1.4058
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.1096	-0.5268	-0.0025	-0.1232	-0.0383	-0.0438	0.0028	-0.1136
	(0.0000)***	(0.0037)**	(0.8879)	(0.0000)***	(0.0000)***	(0.0068)***	(0.0099)***	(0.0000)***
β_4	-0.7234	-0.4510	-0.0200	-0.1084	-0.0503	-0.2499	-0.0050	-0.0858
	(0.0009)***	(0.0004)***	(0.0000)***	(0.1107)	(0.1676)	(0.0017)***	(0.0076)***	(0.7497)
F_1 (H_0: $\beta_1 = \beta_2$)	6.7734	5.3030	0.0019	5.2409	1.6255	11.5576	20.4128	0.0002
	(0.0094)***	(0.0214)**	(0.9656)	(0.0222)**	(0.2026)	(0.0007)***	(0.0000)***	(0.9882)
F_2 (H_0: $\beta_3 = \beta_4$)	8.1745	0.1304	0.9754	0.0507	0.1105	7.3255	15.8129	0.0109
	(0.0043)***	(0.7181)	(0.3235)	(0.8219)	(0.7396)	(0.0069)***	(0.0001)***	(0.9171)
R^2_{adj}	0.5570	0.6651	0.7293	0.5266	0.6801	0.5643	0.3966	0.6101
Panel D: Herding estimations controlling for the effect of US market returns								
β_0	0.2678	0.2623	0.3687	0.9760	0.5494	1.1705	0.0050	0.5356
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.4599	1.5874	0.7699	1.0088	0.7067	0.8165	0.0074	1.3951
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	-0.1022	-0.1599	-0.0199	-0.1421	-0.0384	-0.0535	0.0009	-0.1130
	(0.0000)***	(0.1232)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0005)***	(0.3836)	(0.0000)***
β_3	0.0233	-0.0001	-0.0819	-0.0227	0.0237	-0.0059	0.0003	0.0167
	(0.0010)***	(0.9774)	(0.0000)***	(0.0000)***	(0.0000)***	(0.2379)	(0.0018)***	(0.2013)
R^2_{adj}	0.5586	0.6487	0.7400	0.5225	0.6851	0.5628	0.3871	0.6117
Panel E: Herding estimations controlling for the effect of South African market returns								
β_0	0.2892	0.2625	0.2784	0.9643	0.5614	1.1649	0.0057	0.5686
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.4615	1.5656	0.7705	1.0026	0.7000	0.8224	0.0012	1.3948
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.5582)	(0.0000)***
β_2	-0.1036	-0.1364	-0.0199	-0.1401	-0.0379	-0.0548	0.0046	-0.1123
	(0.0000)***	(0.1903)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0004)***	(0.0004)***	(0.0000)***
β_3	0.00003	-0.0009	0.0146	-0.0044	0.0129	-0.0022	-0.000004	-0.0110
	(0.9956)	(0.8187)	(0.1044)	(0.3144)	(0.0022)***	(0.6319)	(0.9748)	(0.3104)
R^2_{adj}	0.5663	0.6520	0.7309	0.5102	0.6810	0.5661	0.5329	0.6095

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP}) r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH}) r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the pre crisis period (23/1/2002 – 9/10/2007). CSAD refers to the value-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the value-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 7: Crisis period (10/10/2007-6/3/2009) equal-weighted herding estimates for our sample markets

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
Panel A: Unconditional herding estimations								
β_0	0.0765	0.2641	0.0621	1.0365	1.0174	1.5591	0.0779	0.2050
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0060)***	(0.0000)***
β_1	1.6861	1.8116	2.1135	0.7792	0.7186	1.0283	1.7198	2.1673
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0426	-0.4279	-0.4470	-0.1019	-0.0939	-0.2919	-0.2516	-0.3244
	(0.3741)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0017)***	(0.0000)***	(0.0000)***
R^2_{adj}	0.9014	0.7217	0.8551	0.6200	0.4491	0.1969	0.8906	0.7886
Panel B: Herding estimations conditional on market returns								
β_0	0.0772	0.2486	0.0634	1.0452	1.0061	1.5865	0.0782	0.2039
	(0.0000)***	(0.0000)***	(0.0004)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0060)***	(0.0000)***
β_1	1.6330	1.8382	2.0695	0.8073	0.8824	1.4279	1.6605	2.2300
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.7081	1.9913	2.1635	0.7172	0.6419	0.4684	1.7973	2.1156
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0291)**	(0.0000)***	(0.0000)***
β_3	0.0914	-0.4221	-0.4306	-0.1116	-0.1445	-0.5329	-0.2248	-0.3424
	(0.2307)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0002)***	(0.0000)***
β_4	0.0230	-0.5860	-0.4559	-0.0744	-0.0740	0.0480	-0.2829	-0.3071
	(0.6680)	(0.0000)***	(0.0000)***	(0.0061)***	(0.0000)***	(0.6860)	(0.0006)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	0.5103	2.1959	0.7139	1.9536	9.0171	25.2221	1.4722	0.7244
	(0.4756)	(0.1394)	(0.3987)	(0.1631)	(0.0029)***	(0.0000)***	(0.2265)	(0.3954)
F_2 (H_0: $\beta_3 = \beta_4$)	0.6854	7.2372	0.0521	1.8206	6.5023	20.9840	0.5029	0.3753
	(0.4084)	(0.0075)***	(0.8196)	(0.1781)	(0.0113)**	(0.0000)***	(0.4791)	(0.5406)
R^2_{adj}	0.9010	0.7278	0.8551	0.6200	0.4615	0.2494	0.8908	0.7877
Panel C: Herding estimations conditional on market volatility								
β_0	0.0653	0.2200	0.0628	1.0748	0.9171	1.5141	0.1215	0.2147
	(0.0059)***	(0.0000)***	(0.0111)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0031)***	(0.0001)***
β_1	1.6842	1.6305	2.1504	0.7468	0.7130	1.0184	1.6633	2.1797
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.8280	2.1595	2.1769	0.5344	1.1179	1.2753	1.3542	2.1216
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0011)***	(0.0000)***	(0.0000)***
β_3	0.0482	-0.3631	-0.4727	-0.0968	-0.0856	-0.2707	-0.2355	-0.3291
	(0.3438)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0092)***	(0.0000)***	(0.0000)***
β_4	-0.0750	-0.7081	-0.8493	0.1227	-0.2382	-0.4823	0.1643	-0.3168
	(0.9252)	(0.0000)***	(0.2031)	(0.3815)	(0.0279)**	(0.1363)	(0.6136)	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	0.2840	11.7544	0.0114	2.3993	7.6520	0.6631	2.2136	0.1442
	(0.5945)	(0.0007)***	(0.9149)	(0.1223)	(0.0060)***	(0.4160)	(0.1384)	(0.7044)
F_2 (H_0: $\beta_3 = \beta_4$)	0.0248	5.0419	0.3373	2.6094	2.1473	0.4832	1.7319	0.0256
	(0.8750)	(0.0254)**	(0.5617)	(0.1072)	(0.1439)	(0.4875)	(0.1897)	(0.8731)
R^2_{adj}	0.9011	0.7317	0.8551	0.6207	0.4709	0.1938	0.8908	0.7873
Panel D: Herding estimations controlling for the effect of US market returns								
β_0	0.0726	0.2702	0.6030	1.0376	0.9887	1.6428	0.0805	0.2061
	(0.0000)***	(0.0000)***	(0.0004)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0068)***	(0.0001)***
β_1	1.6808	1.8101	2.1251	0.7808	0.6931	0.9418	1.7163	2.1667
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0465	-0.4277	-0.4533	-0.1020	-0.0961	-0.2401	-0.2502	-0.3242
	(0.3333)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0076)***	(0.0000)***	(0.0000)***
β_3	0.0007	-0.0010	-0.0005	-0.0004	0.0103	-0.0117	-0.0002	-0.0002
	(0.2660)	(0.3274)	(0.4742)	(0.7243)	(0.0000)***	(0.0000)***	(0.7669)	(0.9424)
R^2_{adj}	0.9015	0.7216	0.8549	0.6190	0.5000	0.2573	0.8901	0.7879
Panel E: Herding estimations controlling for the effect of South African market returns								
β_0	0.0724	0.2731	0.0575	1.0327	1.0162	1.6856	0.0156	0.2027
	(0.0000)***	(0.0000)***	(0.0013)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.7940)	(0.0001)***
β_1	1.6936	1.8009	2.0867	0.7729	0.6823	0.9272	1.8969	2.1692
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0396	-0.4249	-0.4310	-0.1009	-0.0931	-0.2404	-0.3327	-0.3235
	(0.4139)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0077)***	(0.0004)***	(0.0000)***
β_3	0.0007	-0.0014	0.0022	0.0016	0.0079	-0.0214	0.0122	-0.0003
	(0.5194)	(0.4595)	(0.1007)	(0.4156)	(0.0257)**	(0.0000)***	(0.0008)***	(0.9341)
R^2_{adj}	0.9011	0.7209	0.8565	0.6178	0.4562	0.2555	0.8996	0.7871

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP}) r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH}) r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the crisis period (10/10/2007-6/3/2009). CSAD refers to the equal-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the equal-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 8: Crisis period (10/10/2007-6/3/2009) value-weighted herding estimates for our sample markets

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
Panel A: Unconditional herding estimations								
β_0	0.1742	0.3846	0.2017	1.1207	1.1072	1.8483	0.0028	0.6211
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.0703	1.1583	1.0388	0.5926	0.6050	0.4056	0.0079	1.4362
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0017)***	(0.0000)***	(0.0000)***
β_2	0.0133	0.2192	-0.0378	-0.0540	-0.0545	-0.0332	0.0031	-0.1250
	(0.4357)	(0.2772)	(0.0000)***	(0.0000)***	(0.0000)***	(0.4416)	(0.0043)***	(0.0000)***
R^2_{adj}	0.8423	0.6658	0.9461	0.6180	0.4730	0.1508	0.7373	0.5328
Panel B: Herding estimations conditional on market returns								
β_0	0.1664	0.3901	0.1234	1.1310	1.1066	1.8540	0.0037	0.5983
	(0.0000)***	(0.0000)***	(0.0018)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.2358	1.2867	1.0285	0.6176	0.6893	0.7948	0.0044	1.4583
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0111)**	(0.0000)***
β_2	1.0627	0.9121	1.1647	0.5341	0.5338	0.1465	-0.0012	1.5782
	(0.0000)***	(0.0024)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.2871)	(0.6132)	(0.0000)***
β_3	-0.0963	0.0719	-0.0360	-0.0590	-0.0705	-0.1883	0.0042	-0.1223
	(0.0561)*	(0.7628)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0019)***	(0.0001)***	(0.0000)***
β_4	0.0207	0.4928	-0.0525	-0.0372	-0.0407	0.0604	0.0141	-0.1664
	(0.2496)	(0.0854)*	(0.0000)***	(0.0139)**	(0.0045)***	(0.2024)	(0.0000)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	2.8710	1.4797	45.4020	2.6646	5.0635	19.9280	7.1102	0.6216
	(0.0913)*	(0.2248)	(0.0000)***	(0.1035)	(0.0251)**	(0.0000)***	(0.0083)***	(0.4311)
F_2 (H_0: $\beta_3 = \beta_4$)	5.2590	1.7485	64.4684	2.1364	2.7126	15.0207	24.4723	3.0974
	(0.0226)**	(0.1870)	(0.0000)***	(0.1448)	(0.1006)	(0.0001)***	(0.0000)***	(0.0795)*
R^2_{adj}	0.8442	0.6656	0.9542	0.6188	0.4793	0.1953	0.7934	0.5382
Panel C: Herding estimations conditional on market volatility								
β_0	0.1562	0.3523	0.1195	1.1416	1.0856	1.9789	0.0032	0.5521
	(0.0000)***	(0.0000)***	(0.0035)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.0384	1.3099	-3.5425	0.5819	0.5835	0.3543	0.0070	1.3139
	(0.0000)***	(0.0234)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0124)**	(0.0002)***	(0.0000)***
β_2	1.1334	1.5447	1.1714	0.4949	0.6364	-0.2170	0.0035	1.8289
	(0.0001)***	(0.0000)***	(0.0000)***	(0.0004)***	(0.0003)***	(0.4288)	(0.2761)	(0.0000)***
β_3	0.0233	0.2491	2.8614	-0.0529	-0.0492	-0.0352	0.0034	-0.1093
	(0.1770)	(0.6353)	(0.0000)***	(0.0000)***	(0.0001)***	(0.4519)	(0.0038)***	(0.0000)***
β_4	0.4519	-0.3254	-0.0491	0.0132	-0.0295	0.3460	0.0099	-0.2773
	(0.3071)	(0.1687)	(0.0000)***	(0.8932)	(0.7344)	(0.0332)**	(0.0113)**	(0.1066)
F_1 (H_0: $\beta_1 = \beta_2$)	0.1366	0.1560	49.7670	0.5307	0.1296	6.5463	1.6860	3.7578
	(0.7120)	(0.6932)	(0.0000)***	(0.4668)	(0.7191)	(0.0110)**	(0.1957)	(0.0536)*
F_2 (H_0: $\beta_3 = \beta_4$)	0.9582	1.0505	36.0865	0.4751	0.0550	6.3325	3.0992	0.9781
	(0.3285)	(0.3062)	(0.0000)***	(0.4911)	(0.8148)	(0.0123)**	(0.0799)*	(0.3235)
R^2_{adj}	0.8475	0.6854	0.9525	0.6164	0.4740	0.1624	0.7393	0.5392
Panel D: Herding estimations controlling for the effect of US market returns								
β_0	0.1712	0.3972	0.2078	1.1175	1.0345	1.9214	0.0028	0.6237
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.0697	1.1476	1.0428	0.5914	0.6065	0.3439	0.0078	1.4356
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0056)***	(0.0000)***	(0.0000)***
β_2	0.0136	0.2238	-0.0379	-0.0542	-0.0573	0.0044	0.0031	-0.1249
	(0.4281)	(0.2674)	(0.0000)***	(0.0000)***	(0.0000)***	(0.9157)	(0.0043)***	(0.0000)***
β_3	0.0005	-0.0016	-0.0029	0.0008	0.0145	-0.0134	-0.000002	-0.0005
	(0.6439)	(0.3020)	(0.0924)*	(0.4847)	(0.0000)***	(0.0000)***	(0.8640)	(0.8994)
R^2_{adj}	0.8418	0.6659	0.9464	0.6174	0.5509	0.2202	0.7360	0.5312
Panel E: Herding estimations controlling for the effect of South African market returns								
β_0	0.1853	0.3899	0.2039	1.1083	1.0778	1.9514	0.0037	0.5848
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0050)***	(0.0000)***
β_1	1.0756	1.1908	1.0574	0.5973	0.5767	0.3824	0.0051	1.4019
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0021)***	(0.3236)	(0.0000)***
β_2	0.0115	0.1928	-0.0384	-0.0549	-0.0557	-0.0190	0.0068	-0.1213
	(0.5043)	(0.3484)	(0.0000)***	(0.0000)***	(0.0000)***	(0.6475)	(0.0579)*	(0.0000)***
β_3	-0.0027	-0.0019	-0.0118	0.0019	0.0161	-0.0234	0.000007	0.0106
	(0.1545)	(0.5234)	(0.0003)***	(0.3514)	(0.0000)***	(0.0000)***	(0.9237)	(0.0538)*
R^2_{adj}	0.8424	0.6672	0.9465	0.6288	0.5037	0.2175	0.6746	0.5369

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP}) r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH}) r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the crisis period (10/10/2007-6/3/2009). CSAD refers to the value-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the value-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 9: Post crisis period (7/3/2009-15/7/2015) equal-weighted herding estimates for our sample markets

Panel A: Unconditional herding estimations

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
β_0	0.0689	0.4782	0.2608	1.0835	0.5582	0.7476	0.1023	0.1818
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.7656	1.5605	2.0794	0.7536	1.0168	1.4465	1.8937	2.1189
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0479	-0.4256	-0.5145	-0.0855	-0.1261	-0.1995	-0.3411	-0.2992
	(0.0487)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
R^2_{adj}	0.8970	0.4819	0.7655	0.3839	0.5258	0.6339	0.8267	0.7848

Panel B: Herding estimations conditional on market returns

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
β_0	0.0662	0.4772	0.2610	1.0922	0.5576	0.7486	0.1013	0.1830
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.6681	1.6354	2.0106	0.7781	1.0376	1.4852	1.8703	2.0932
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	2.0254	1.4997	2.1530	0.6109	0.9945	1.4077	1.9424	2.1311
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	0.0977	-0.5020	-0.4769	-0.1002	-0.1289	-0.1811	-0.3374	-0.2993
	(0.0001)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0012)***	(0.0000)***	(0.0000)***
β_4	-0.1754	-0.3757	-0.5534	0.0312	-0.1245	-0.2142	-0.3428	-0.2839
	(0.0064)***	(0.0000)***	(0.0000)***	(0.5373)	(0.0001)***	(0.0000)***	(0.0000)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	40.7116	2.7777	6.4727	8.7818	0.7297	1.1773	1.3188	0.3037
	(0.0000)***	(0.0958)*	(0.0110)**	(0.0031)***	(0.3931)	(0.2781)	(0.2511)	(0.5817)
F_2 (H_0: $\beta_3 = \beta_4$)	17.7269	1.6808	4.2845	6.8848	0.0182	0.2555	0.0139	0.1436
	(0.0000)***	(0.1950)	(0.0386)**	(0.0088)***	(0.8928)	(0.6133)	(0.9063)	(0.7048)
R^2_{adj}	0.9003	0.4822	0.7661	0.3865	0.5258	0.6360	0.8271	0.7851

Panel C: Herding estimations conditional on market volatility

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
β_0	0.0639	0.4709	0.3084	1.0937	0.5335	0.7124	0.1336	0.1710
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.7548	1.5612	2.0342	0.7237	1.0087	1.2709	1.8253	2.0889
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.8488	1.6546	1.5072	0.6150	1.1730	1.8355	1.4671	2.1648
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	0.0571	-0.4161	-0.5068	-0.0768	-0.1206	-0.0794	-0.3186	-0.2847
	(0.0207)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0527)*	(0.0000)***	(0.0000)***
β_4	0.0560	-0.5632	0.4361	0.2034	-0.1878	-0.0769	0.4938	-0.2025
	(0.7543)	(0.0013)***	(0.0806)*	(0.1604)	(0.0000)***	(0.5862)	(0.0157)**	(0.3273)
F_1 (H_0: $\beta_1 = \beta_2$)	1.4650	0.7747	17.8415	1.4149	4.8740	34.8909	9.4693	0.2851
	(0.2263)	(0.3789)	(0.0000)***	(0.2344)	(0.0274)**	(0.0000)***	(0.0021)***	(0.5935)
F_2 (H_0: $\beta_3 = \beta_4$)	0.00004	0.7289	15.0378	3.9324	0.8678	0.0004	16.7758	0.1655
	(0.9948)	(0.3934)	(0.0001)***	(0.0475)**	(0.3517)	(0.9849)	(0.0000)***	(0.6842)
R^2_{adj}	0.8972	0.4815	0.7677	0.3852	0.5289	0.6681	0.8294	0.7854

Panel D: Herding estimations controlling for the effect of US market returns

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
β_0	0.0698	0.4918	0.2587	1.0789	0.5633	0.7426	0.1058	0.1826
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.7660	1.5598	2.0774	0.7475	1.0115	1.4454	1.8916	2.1195
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0478	-0.4271	-0.5137	-0.0851	-0.1188	-0.2017	-0.3400	-0.2994
	(0.0495)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	-0.0008	-0.0121	0.0022	0.0060	-0.0050	0.0050	-0.0031	-0.0008
	(0.4884)	(0.0000)***	(0.3421)	(0.0126)**	(0.1022)	(0.0401)**	(0.2825)	(0.8289)
R^2_{adj}	0.8970	0.4884	0.7654	0.3859	0.5263	0.6346	0.8268	0.7847

Panel E: Herding estimations controlling for the effect of South African market returns

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
β_0	0.0652	0.4893	0.2626	1.0833	0.5608	0.7312	0.1195	0.1805
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.7629	1.5483	2.0671	0.7277	1.0161	1.4371	1.7706	2.1236
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0499	-0.4189	-0.5087	-0.0781	-0.1252	-0.2097	-0.2733	-0.3007
	(0.0420)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	0.0040	-0.0098	0.0016	0.0110	-0.0016	0.0183	-0.0016	-0.0009
	(0.0478)**	(0.0089)***	(0.6333)	(0.0018)***	(0.7155)	(0.0000)***	(0.8545)	(0.8571)
R^2_{adj}	0.8973	0.4835	0.7641	0.3860	0.5242	0.6385	0.8219	0.7850

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP}) r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH}) r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the post crisis period (7/3/2009-15/7/2015). CSAD refers to the equal-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the equal-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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Table 10: Post crisis period (7/3/2009-15/7/2015) value-weighted herding estimates for our sample markets

	Botswana	BRVM	Ghana	Kenya	Namibia	Nigeria	Tanzania	Zambia
Panel A: Unconditional herding estimations								
β_0	0.1565	0.5226	0.6848	1.1230	0.6198	0.8093	0.0024	0.5421
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.1903	0.9934	0.8495	0.6239	0.7347	0.9417	0.0110	1.3714
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0176	0.2065	0.0177	-0.0584	-0.0576	-0.0717	0.0008	-0.1187
	(0.2419)	(0.0048)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0866)*	(0.0000)***
R^2_{adj}	0.6809	0.6501	0.8559	0.3879	0.5605	0.7640	0.7292	0.5837
Panel B: Herding estimations conditional on market returns								
β_0	0.1515	0.5248	0.5915	1.1246	0.6193	0.8100	0.0026	0.5418
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.1570	0.9488	1.0016	0.6283	0.7599	0.9613	0.0094	1.3739
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.3509	1.0072	0.8812	0.5998	0.7108	0.9170	0.0088	1.3746
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	0.0321	0.2322	-0.0407	-0.0613	-0.0607	-0.0802	0.0014	-0.1207
	(0.0416)**	(0.0042)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0038)***	(0.0000)***
β_4	-0.0839	0.2173	-0.0179	-0.0422	-0.0570	-0.0607	0.0039	-0.1175
	(0.0362)**	(0.0448)**	(0.0000)***	(0.0687)*	(0.0005)***	(0.0000)***	(0.0002)***	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	9.3042	0.3518	57.5736	0.4806	1.6255	1.8374	0.3420	0.0001
	(0.0023)**	(0.5532)	(0.0000)***	(0.4882)	(0.2025)	(0.1754)	(0.5588)	(0.9919)
F_2 (H_0: $\beta_3 = \beta_4$)	7.9484	0.0183	134.0200	0.6380	0.0495	1.9286	5.8886	0.1008
	(0.0049)**	(0.8925)	(0.0000)***	(0.4245)	(0.8240)	(0.1651)	(0.0154)**	(0.7509)
R^2_{adj}	0.6826	0.6502	0.8673	0.3873	0.5613	0.7640	0.7361	0.5833
Panel C: Herding estimations conditional on market volatility								
β_0	0.1255	0.4726	0.4546	1.1233	0.5689	0.7596	0.0022	0.5163
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.1836	0.8298	-4.3472	0.6288	0.7307	0.9037	0.0101	1.3101
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	1.6776	1.5004	1.1119	0.6289	0.9761	1.1480	0.0129	1.7716
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_3	0.0250	0.4318	4.0441	-0.0596	-0.0525	-0.0538	0.0014	-0.1099
	(0.0987)*	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0041)***	(0.0000)***
β_4	-0.3478	-0.5090	-0.0482	-0.0813	-0.1568	-0.0968	-0.0001	-0.2319
	(0.3479)	(0.0002)***	(0.0000)***	(0.2254)	(0.0000)***	(0.0287)**	(0.9237)	(0.0000)***
F_1 (H_0: $\beta_1 = \beta_2$)	12.1372	27.9232	199.3381	0.000005	22.1658	21.2106	6.9313	25.9473
	(0.0005)***	(0.0000)***	(0.0000)***	(0.9983)	(0.0000)***	(0.0000)***	(0.0086)***	(0.0000)***
F_2 (H_0: $\beta_3 = \beta_4$)	1.0259	38.4073	506.3915	0.1096	9.8391	1.0269	1.8538	25.0797
	(0.3113)	(0.0000)***	(0.0000)***	(0.7406)	(0.0017)***	(0.3110)	(0.1736)	(0.0000)***
R^2_{adj}	0.6873	0.6589	0.8901	0.3873	0.5673	0.7740	0.7318	0.5921
Panel D: Herding estimations controlling for the effect of US market returns								
β_0	0.1558	0.5361	0.6745	1.1172	0.6175	0.8056	0.0024	0.5416
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.1901	0.9866	0.8485	0.6219	0.7365	0.9402	0.0110	1.3712
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0177	0.2097	-0.0176	-0.0593	-0.0588	-0.0715	0.0008	-0.1187
	(0.2401)	(0.0041)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0852)*	(0.0000)***
β_3	0.0006	-0.0106	0.0107	0.0064	0.0020	0.0041	-0.00003	0.0005
	(0.7633)	(0.0004)***	(0.0268)**	(0.0119)**	(0.5578)	(0.1037)	(0.5372)	(0.9235)
R^2_{adj}	0.6807	0.6528	0.8562	0.3899	0.5603	0.7642	0.7291	0.5834
Panel E: Herding estimations controlling for the effect of South African market returns								
β_0	0.1538	0.5330	0.4357	1.1259	0.6210	0.7960	0.0022	0.5349
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	1.1907	0.9835	1.0781	0.5997	0.7297	0.9321	0.0108	1.3675
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.0177	0.2149	-0.0447	-0.0532	-0.0574	-0.0702	0.0010	-0.1181
	(0.2443)	(0.0034)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.2155)	(0.0000)***
β_3	0.0029	-0.0115	0.0011	0.0101	0.0031	0.0164	0.0001	0.0053
	(0.4052)	(0.0048)***	(0.8585)	(0.0076)***	(0.5353)	(0.0000)***	(0.4464)	(0.4598)
R^2_{adj}	0.6795	0.6563	0.8967	0.3837	0.5593	0.7679	0.7847	0.5849

The table presents the estimates from the following equations:

Panel A: $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{UP}|r_{m,t}| + \beta_2(1- D_t^{UP})|r_{m,t}| + \beta_3 D_t^{UP} r^2_{m,t} + \beta_4(1- D_t^{UP})r^2_{m,t} + \varepsilon_t$

Panel C: $CSAD_{m,t} = \beta_0 + \beta_1 D_t^{HIGH}|r_{m,t}| + \beta_2(1- D_t^{HIGH})|r_{m,t}| + \beta_3 D_t^{HIGH} r^2_{m,t} + \beta_4(1- D_t^{HIGH})r^2_{m,t} + \varepsilon_t$

Panel D: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{US,t} + \varepsilon_t$

Panel E: $CSAD_{m,t} = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r^2_{m,t} + \beta_3 r^2_{SA,t} + \varepsilon_t$

All estimations involve Newey-West consistent estimators and pertain to the post crisis period (7/3/2009-15/7/2015). CSAD refers to the value-weighted cross sectional absolute deviation of returns; $r_{m,t}$ is the value-weighted average market return; D_t^{UP} is a dummy variable, assuming the value of unity during up-market days (i.e. days with $r_{m,t} > 0$), and zero during down-market days (i.e. days with $r_{m,t} < 0$); D_t^{HIGH} is a dummy variable, assuming the value of unity during high volatility days, and zero during low volatility days; the subscript "US" denotes the returns of the US market, the latter proxied here through the S&P 500 index; the subscript "SA" denotes the returns of the South African market, proxied here through the FTSE/JSE All Share index. The F_1 and F_2 test statistics test the following null hypotheses, respectively: H_0: $\beta_1 = \beta_2$ and H_0: $\beta_3 = \beta_4$. Figures in brackets are p-values. * indicates significance at the 10 percent significance level; ** indicates significance at the 5 percent significance level and *** indicates significance at the 1 percent significance level.

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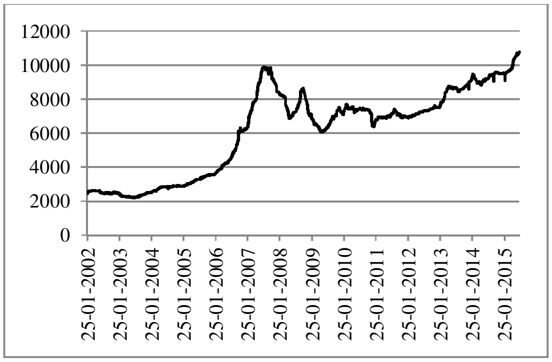
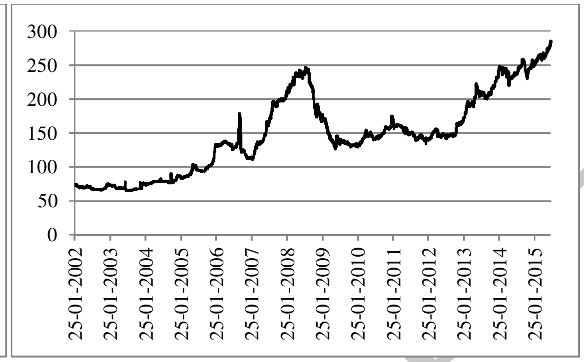
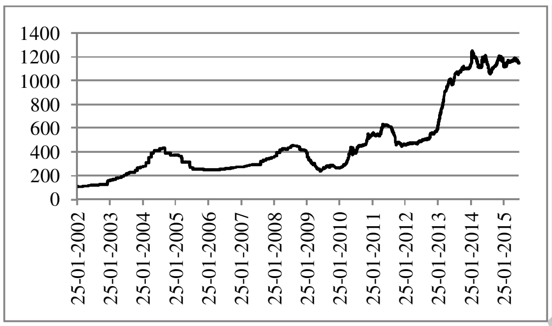
Figure 1: Representative index charts from the eight sample markets.



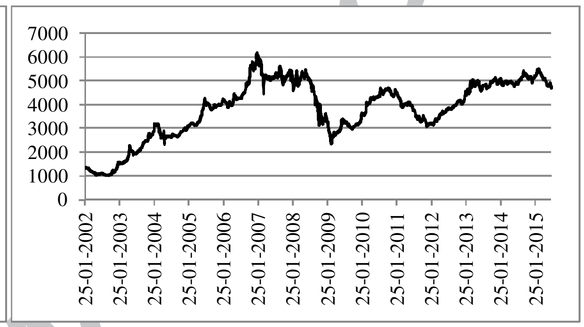
(a): Botswana Domestic Companies Index



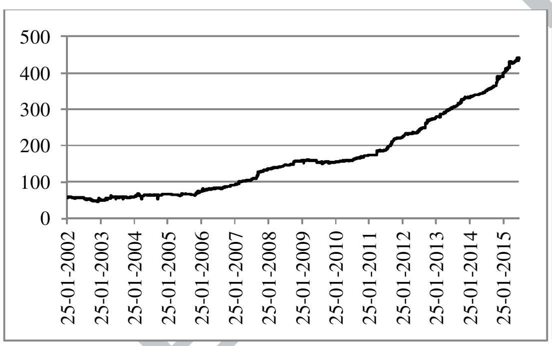
(b): BRVM Composite Index



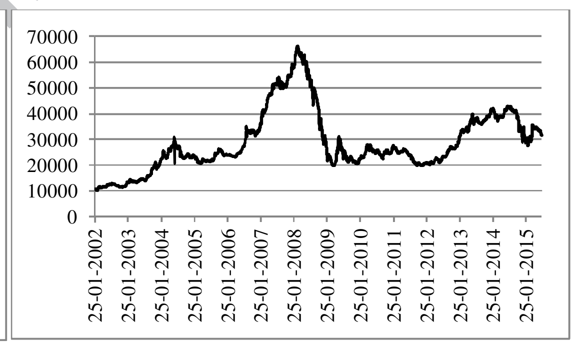
(c): S&P Ghana BMI Index



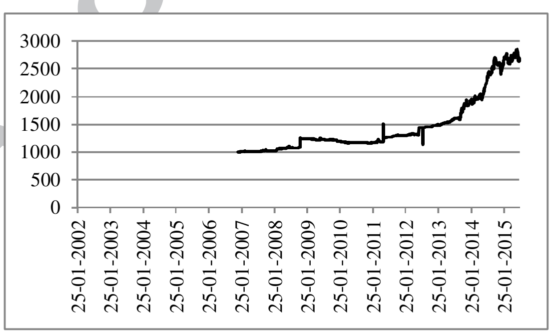
(d): Kenya NSE20 Index



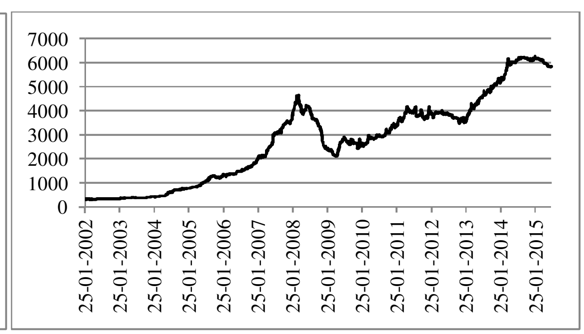
(e): FTSE Namibia Local Index



(f): Nigeria All Share Index



(g): Dar Es Salaam (DSE) Index



(i): Zambia Lusaka All Share Index

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Herding in Frontier Markets: Evidence from African Stock Exchanges

Highlights

1) We study herding in eight African markets for the January 2002 - July 2015 period.
2) Herding is significant, with smaller stocks found to enhance its magnitude.
3) Asymmetric herding is motivated by market volatility, yet not market performance.
4) Herding asymmetries grow weak when accounting for the 2007-2009 crisis.
5) Herding in African markets is not strongly driven by non-domestic factors.

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