Herding Behavior in African Stock Markets: A State-Space Assessment During Times of Crisis

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Current version: August 2024

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Abstract

This study examines investor herding behavior in 17 African stock markets from 2009 to 2022, focusing on herding dynamics during crises (such as the European Debt Crisis, Arab Spring uprising, Ebola outbreak, Brexit, and Covid-19 pandemic). Using state-space models to extract time series of herd dynamics, we observe statistically significant but slightly negative/adverse herding during normal times. Interestingly, there is no evidence of increased herding behavior in African markets during recent hard times. However, short-lived highly pronounced episodes of adverse herding occur during crisis periods, with external crises having greater impact on herding than internal crises in Africa.

JEL classification: C12, C32, G15, G41

Keywords: African stock markets, Herding behavior, State-space model, Crisis.

1. Introduction

Herding behavior refers to the tendency of some investors to imitate the actions of others rather than relying on their own analysis.[1] This phenomenon becomes particularly relevant during times of crisis, uncertainty, or panic, when market volatility and the influx of fuzzy information can undermine the accuracy and reliability of investment models. African stock markets, like other emerging and frontier markets, often face challenges related to inexperienced participants, lower information quality, poor information diffusion, transparency deficiencies, and higher information asymmetry, which increase the costs of information acquisition (Adeabah et al., 2023; Guney, Kallinterakis, and Komba, 2017). Consequently, investors may attempt to reduce their costs by suppressing their own beliefs and relying on inferences or tracking their peers' transactions. Furthermore, unexpected shocks resulting from the various crises over the last decades can alter the investors' beliefs and lead to trades that disregard the risk-return equilibrium relationship and align individual asset returns with overall market performance (Xing, Cheng, and Sun, 2024; Messis, Alexandridis, and Zapranis, 2023; Hwang, Rubesam, and Salmon, 2021; Hwang and Salmon, 2004). Even in calm market conditions, overconfidence introduces distortions in the risk-return relationship due to herding behavior by investors (Hwang et al., 2021).

Despite the potential impact of herding behavior on asset returns, research on herding in frontier markets remains limited, especially in Africa (Komalasari et al., 2021). The existing literature has investigated the herding behavior of investors in some specific African stock markets, with various results: Boadi et al. (2021) in Ghana, Seetharam and Britten

[1] For the various typologies of herding, see Komalasari et al. (2021), Indārs, Savin, and Lublóy (2019), and Bikhchandani and Sharma (2000).

(2013) and Kunjal and Peerbhai (2021) in South Africa, Ferrouhi (2021) in Morocco, and Guney et al. (2017) in eight African frontier markets.

This paper investigates the extent to which the herding behavior of investors in a comprehensive set of 17 African markets is affected by the major crises that adversely impact the economic activities and create periods of higher uncertainty over the span of 2009-2022. It focuses on five major crises: The Eurozone sovereign debt crisis (EDC), the Arab Spring uprising (ASC), the Ebola outbreak (EBC), the Brexit (BXT), and the Covid-19 pandemic (CVD). How do investors in African stock markets respond during these challenging periods characterized by fear, anxiety, rumors, information asymmetry, and market disruptions? Despite the crucial significance of this research question for financial risk management, policy formulation, investment guidance, and market development, there exists a noticeable lack of robust evidence regarding the impact of crises on herding behavior within African equity markets.[2] For instance, in the context of external shocks caused by the Covid-19 pandemic, Del Lo, Basséne and Séne (2022) present evidence that African financial markets have exhibited heightened volatility due to the disease's progression rather than mere panic and fear. Kunjal and Peerbhai (2021) investigate the impact of the COVID-19 pandemic on herding behaviour within the South African ETF market. Their findings contradict the notion of herd behavior during this challenging period. In contrast, Del Giudice and Paltrinieri (2017) reveal that retail investors exhibited collective overreac-

[2] Elsewhere, recent studies have investigated herding during the Covid-19 pandemic in various markets, including major Asian stock markets (Ferreruela, Kallinterakis, and Mallor, 2022; Jiang et al., 2022), Australia (Espinosa-Méndez and Arias, 2021a; Huynh, Nguyen, and Tran, 2024), China (Wu, Yang and Zhao, 2020; Xing, Cheng and Sun, 2024; Yang and Chuang, 2023), Europe (Espinosa-Méndez and Arias, 2021b), Hong Kong (Wen, Yang and Jiang, 2022), Spain and Portugal (Ferreruela and Mallor, 2021).

tions that significantly affected mutual fund flows to Africa during the tumultuous times of the Ebola outbreak and the Arab Spring unrest.

The divergent results from prior studies prompt intriguing inquiries into the intricacies of investor decision-making within African financial markets. We explore whether conditions of heightened uncertainty and turmoil are associated with increased herding tendencies. Additionally, we examine potential differences in herding behavior across various crisis contexts, including financial crises (such as the Eurozone sovereign debt crisis), political crises (such as Brexit and the Arab Spring uprising), and health crises (such as the Ebola outbreak and the Covid-19 pandemic). We also consider how the impact of external crises (Brexit and the Eurozone sovereign debt crises) on herding behavior differs from that of internal crises (the Arab Spring uprising, the Ebola outbreak, and the Covid-19 pandemic).

While existing research on herding in African stock markets relies on the cross-sectional standard or absolute deviations of returns using the models of Christie and Huang (1995) and Chang, Cheng, and Khorana (2000), the restrictive and static nature of these models has been questioned by Arjoon and Bhatnagar (2017) and Hwang and Salmon (2004) who emphasize the need for more dynamic approaches. We contribute to the literature by assessing herding based on the state-space model which allows the detection of time-varying regular and adverse herding (Messis, Alexandridis, and Zapranis, 2023; Jùnior et al., 2020; Nath and Brooks, 2020; Raimundo Jùnior et al., 2020). This is important as many African stock markets are still developing and undergoing regulatory changes, and herding behavior may vary over time. To the best of our knowledge, this is the first study to use the state-space model to gauge the dynamic of herding behavior in African markets. The study contributes to sharpen our understanding of investors in African markets where size and liquidity, along with the degree of market sophistication can significantly affect investors' behavior especially during hard times.

We draw on a comprehensive set of 1,241 stocks from the main 17 African stock exchanges to assess the time dynamic of herding behavior in these markets from January 5, 2009, to December 30, 2022. We find evidence of statistically significant but slightly negative herding in almost all the markets during normal time. There is no evidence of an increase in investors' herding behavior in African markets during recent bad times. In contrast, there are many episodes of more pronounced but short-lived adverse herding that are largely related to periods of crisis. Internally originated crises did not lead to more herding in any of the African country, compared to external crises. Health crises and political crises have significant impact on herding behavior in different countries.

The remainder of the paper is organized as follows. Section 2 outlines the methodology and Section 3 presents the data and the summary descriptive statistics on the markets. We discuss the empirical evidence on herding in Section 4, while Section 5 concludes.

2. Methodology

We employ the methodology proposed by Hwang and Salmon (2004), which centers around assessing the cross-sectional dispersion of factor sensitivities. This approach enables us to investigate market herd dynamics over time (Ferreruela et al., 2022; Júnior et al., 2020; Nath and Brooks, 2020; Raimundo Júnior et al., 2020). This is a departure from other methods that depend on the cross-sectional dispersion of returns (Christie and

Huang, 1995; Chang et al., 2000) or on a correlated trading across homogeneous groups of investors (Lakonishok, Shleifer, and Vishny, 1992).[3]

We assume that (i) the conditional market risk premium ($E_t[r_{Mt}]$) is correctly set by a common market-wide view held by all investors, and (ii) the capital assets are priced in equilibrium according to the following conditional version of the CAPM:

$$E_t[r_{it}] = \beta_{it} E_t[r_{Mt}], \tag{1}$$

where $E_t[.]$ denotes the conditional expectations operator, r_{it} is the excess (relative to the riskless rate) stock return at time t, r_{Mt} is the excess market return, and β_{it} is the stock's true conditional market beta. The presence of herding by investors distorts the measurements of the stock's conditional beta and risk premium. The market's biased conditional expectation about the stock's beta at time t (β_{it}^b) can be represented as:

$$\beta_{it}^b = \frac{E_t^b[r_{it}]}{E_t[r_{Mt}]} = \beta_{it} - h_{Mt} \ \beta_{it} - 1 \ = (1 - h_{Mt})\beta_{it} + h_{Mt} \ \beta_{Mt} \ , \tag{2}$$

where $E_t^b[r_{it}]$ is the market's potentially biased conditional expectation of the risk premium at time t, and the weight h_{Mt} is a time-varying market-wide latent parameter capturing the scope of the herding behavior in the market. If $h_{Mt} = 0$, then $\beta_{it}^b = \beta_{it}$ and $E_t^b[r_{it}] = E_t[r_{it}]$, and there is no herding behavior since the relationship given by (1) holds perfectly. As h_{Mt} increases, the intensity of herding increases, and the stock's conditional beta becomes more biased towards the market's true beta. Between 0 and 1, the parame-

[3] As rightly pointed out by Bikhchandani and Sharma (2000) and Hwang and Salmon (2004), the commonly used measures introduced by Christie and Huang (1995) and Chang et al. (2000) are aimed to detect herding only in the asset-specific component of returns, but they miss other forms of herding arising from the common component of returns.

ter h_{Mt} indicates some degree of (positive or regular) herding. As shown by Hwang and Salmon (2004) and Hwang and al. (2021), investors' under-confidence about their signals for the market may lead to an adverse herding with negative value of h_{Mt}.

To estimate the herding measure h_{Mt}, which is unobserved along with the conditional market risk premium, we first compute the cross-sectional deviation of betas ($CSDB$) as:

$$CSDB_t = \sqrt{\frac{\sum_{i=1}^{N_t}\left(\beta_{it}^b - \overline{\beta_{it}^b}\right)^2}{N_t}} \tag{3}$$

where β_{it}^b is the sample estimate of the herding-induced biased beta (β_{it}^b) of stock i for month t, $\overline{\beta_{it}^b} = \frac{1}{N_t}\sum_{i=1}^{N_t}\beta_{it}^b$ is the estimated biased beta of the market for month t, and N_t denotes the number of stocks available in the market in month t. The sample estimate β_{it}^b of biased beta is computed from the following regression using daily excess returns within monthly intervals:

$$r_{it}^d = \alpha_{it} + \beta_{it}^b r_{Mt}^d + \varepsilon_{it}^d, \tag{4}$$

where the superscript d refers to daily data used within month t. We require a stock to be traded for at least ten days during the month to be included in the sample.[4] Equation (2) implies that solely changes in h_{Mt} would drive changes in the CSDB. So, we use the following state-space model to extract h_{Mt} (Model 1 thereafter):

$$\log CSDB_t = \mu + H_{Mt} + \upsilon_{Mt}, \tag{5}$$

[4] The state space model requires equally spaced data, which is a problem especially for Cote d'Ivoire. For this market, we start the *CSDB* estimation in May 2012 since the BRVM market was strongly affected by the second civil war which broke out in March 2011.

$$H_{Mt} = \log\left(1 - h_{Mt}\right) = \phi H_{Mt-1} + \eta_{Mt}, \tag{6}$$

where $\upsilon_{Mt} \sim iid(0, \sigma_{\upsilon}^2)$ and $\eta_{Mt} \sim iid(0, \sigma_{\eta}^2)$. We assume that H_{Mt} follows a dynamic AR(1) process with a zero mean so that a significant value of ϕ indicates the persistence of herding towards the market. Still, the focus is on the parameter σ_{η}, given that its significance is an indication of the existence of herding ($h_{Mt} = 0$ when $\sigma_{\eta} = 0$). We obtain a signal-to-noise ratio (STN) by dividing σ_{η} by the time-series standard deviation of $\log\left(CSDB_t\right)$. This ratio measures the proportion of the variability of the log cross-sectional deviation of beta accounted for by herding.

We further examine the herding behavior after controlling for the market excess returns and volatility. Specifically, we estimate the following unrestricted state-space model (Model 2 thereafter):

$$\log\left(CSDB_t\right) = \mu + H_{Mt} + \lambda R_{Mt} + \gamma \log(\sigma_{Mt}) + \upsilon_{Mt} \tag{7}$$

$$H_{Mt} = \log\left(1 - h_{Mt}\right) = \phi H_{Mt-1} + \eta_{Mt}, \tag{8}$$

where r_{Mt} and σ_{Mt} are the monthly market excess returns and volatility, respectively, with the corresponding coefficients λ and γ. When H_{Mt} and ϕ become insignificant, these control variables indicate that changes in $\log\left(CSDB_t\right)$ are explained by market movements rather than herding.

We estimate the parameters of Model 1 and Model 2 by maximum likelihood using the diffuse Kalman filter algorithm. The dynamic of the herding measure extracted from the state-space model, $h_{Mt} = 1 - \exp(H_{Mt})$, is useful to identify periods of either regular herding ($h_{Mt} > 0$) or adverse herding ($h_{Mt} < 0$).

3. Data

We draw on a comprehensive, survivor-bias-free dataset of daily stock returns and market capitalizations from January 5, 2009, to December 30, 2022, all expressed in US dollars and adjusted for stock splits and dividend payments. The data are retrieved from Datastream and cover all the main 17 African exchanges: Botswana, Cote d'Ivoire, Egypt, Ghana, Kenya, Malawi, Mauritius, Morocco, Namibia, Nigeria, Rwanda, South Africa, Tanzania, Tunisia, Uganda, Zambia, and Zimbabwe.

Following Ince and Porter (2006), and Griffin, Kelly, and Nardari (2010), we apply screening tools to clean the data for errors. Specifically, we restrict the analysis to common stocks by removing non-equity instruments, and retaining only voting classes of stocks.[5] To avoid the impact of outliers, we winsorized returns and market capitalizations at the 0.1% percentile on both sides. Finally, we manually eliminated holidays for which most exchanges are closed on the continent, such as New Year, Christmas, Easter, and Eid.

With these filters applied, we are left with 1,241 stocks from 17 exchanges, representing the most comprehensive sample of African stocks ever studied to the best of our knowledge. Table 1 shows, for each country, region (North and Sub-Saharan Africa) and across the African continent, how the sample has grown from 858 stocks in 2009 to 1,198 stocks in 2022. Because of their low coverage (less than 25 stocks in total) or tiny market capitalization in the case of Zimbabwe, seven Sub-Saharan markets are grouped under the

[5] In case of doubt, we proceed by checking the stock exchange website where the shares are listed and traded, as well as the company's website.

heading "Most Frontier" from here on: Malawi, Namibia, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe.

TABLE 1 ABOUT HERE

Table 2 presents summary descriptive statistics associated with market capitalization, market returns and the cross-sectional standard deviation of the betas (CSDB). In terms of market capitalization, South Africa is the dominant figure in African markets by representing more than 64% (over USD 467 billion) of the total African market capitalization at the end of December 2022. Mauritius and Morocco come in a distant second and third, respectively, with 9.30% and 7.39% of the total market capitalization.

Reflective of a positive market performance of African stock markets during the 2009-2022 period, all average market returns are positive. Tunisia has recorded the weakest market return computed as the continuously compounded monthly average value-weighted returns over the sample period. This could be explained by the severity of the COVID-19 pandemic in this country, as well as the impact of the Arab Spring unrests.[6] At the other extreme, Cote d'Ivoire and the group of the seven Most Frontier markets generated the highest average returns. The associated standard deviations of these returns are reported as "SD1" in Table 2, while "SD2" presents the root square of the monthly market variance, estimated from the sum of the squared daily returns (after subtracting the average daily return in the month) of each market. Reflecting a positive risk-return tradeoff, the

[6] Despite its relatively small population, Tunisia is the third most affected country in Africa in terms of total COVID-19 cases (after South Africa and Morocco) and second in terms of deaths (after South Africa). (Source: https://coronavirus.jhu.edu/region/Tunisia). The Arab Spring crisis also originated from Tunisia where protests arose in December 2010 and the government was overthrown in January 2011.

three most volatile markets over the January 2009 through December 2022 period are the group of Most Frontier markets, the Bourse Regionale des Valeurs Mobilières of Cote d'Ivoire, and Nigeria.

The last columns of Table 2 report the main characteristics of the CSDB. The highest average cross-sectional standard deviation of the betas are observed in Kenya, Ghana, and Morocco, while the smallest values are detected in Cote d'Ivoire and Botswana. CSDB is most (least) volatile in Ghana and Botswana (South Africa and Egypt). Higher CSDB suggests a wider dispersion of systematic risk that may be indicative of a market inefficiency in pricing assets accurately based on their underlying risk exposures, a higher diversification opportunity for investors in the market, and a differing market sentiments or varying expectation among investors.

TABLE 2 ABOUT HERE

4. Empirical results

4.1. Herding towards the market portfolio

Do investors in African stock markets herd towards the market factor? Table 3 presents the results of the estimation of our state space models (Model 1 in Panel A, and Model 2 in Panel B) for herding towards the market portfolios. For each model, we report the aggregated results across all African markets, the North African and the Sub-Saharan markets, the Most Frontier markets, and for the 10 countries with sufficient data for a stand-alone analysis. The model's parameter estimates are reported along with the signal-to-noise ratio (STN) and the statistical properties of the estimated models.

The standard deviation of the state equation residual terms, σ_η, is reported in the fourth column of Table 3 for Model 1. The σ_η estimates range from 0.188 for the Sub-Sahara region to 2.912 for Ghana. They are significantly different from zero for each individual market and the aggregated markets, providing clear evidence of herding towards the market portfolio in the African stock markets. The consistency of herding behavior across all African equity markets strengthens the validity of our findings and suggests that the presence of herding is not limited to specific markets or isolated instances. The results imply that investors in the African stock exchanges are influenced by the actions and choices of other market participants and exhibit a tendency to align their investment decisions with the overall market portfolio. Their behavior leads to a convergence (regular herding) or a divergence (adverse herding) of investment strategies towards the market portfolio, indicating a lack of diversification and a heightened focus on market trends. This is not surprising for emerging, and frontier African markets characterized by low degree of sophistication and liquidity in countries without public financial market traditions (Adeabah et al. 2023).

The stationarity of the herding process is provided by the significant value of the autoregressive parameter ϕ. Over the sample period, the herding persistence parameter ϕ varies from 0.096 for Ghana to 0.599 for Morocco based on Model 1. Except for Ghana and Nigeria where they are not significant, and Botswana (significant only at the 5% level), the estimates of ϕ remain significant at the 1% level for all the other countries and regions. The results also reveal that herding is most persistent in Morocco and Kenya, as well as in the universe of North African countries and the Most Frontier markets.

The signal-to-noise ratios (STN) are very high, ranging from 81.3% for Morocco to 99.7% for Ghana, and revealing that almost all the variability in the cross-sectional standard deviation of betas is explained by the variability of herding.

TABLE 3 ABOUT HERE

Controlling for the market returns and the market volatility as in Model 2 does not materially alter the results: Herding remains significant regardless the state of the market. The statistically significant value of σ_η in Panel B of Table 3 provides the evidence of investor herding behavior in all individual markets and the whole continent. Moreover, Model 2 clearly reveals some of the valuable aspects of the results. First, the impact of the market returns on the CSDB is limited although it is statistically different from zero in Kenya and Mauritius where the cross-sectional deviation of betas increases with the market return. For the whole African continent as well as the North-African region, the impact of the market return (λ) is slightly negative but significant. In contrast, the CSDB is reduced with the higher market volatility condition as the parameter γ is negative and statistically significant except for Botswana and Ghana. For all Africa, a 1% increase in the market volatility leads to a 0.4% reduction in the cross-sectional deviation of stock betas. Comparing the signal-to-noise estimates of Model 2 with those of Model 1, the results show that changes in the CSDB is just marginally explained by the changes in the two fundamental market control variables (market return and market volatility) as the STN is generally lower with Model 2: it is in Morocco, Kenya, and South Africa where market conditions explained a larger part of the herding.

The last two columns of Table 3 provide the log maximum likelihood values (ln(L)) and the Bayesian information criterion (BIC) for Model 2. Compared with those of Model

1, the results show that for almost all the markets, Model 2 is the best fitted model, implying that part of the variation in the cross-sectional standard deviation of betas is explained by market conditions captured through the market returns and volatility.

4.2. Herding during hard times

Following Attig and Sy (2023), ElBannan (2021), and Del Giudice and Paltrinieri (2017), we define the Eurozone sovereign debt crisis (EDC) as spanning over 14 months, from October 2009 to November 2010 when several European countries faced challenges in in repaying or refinancing their public debt. The Arab Spring crisis (ASC) covers the December 2010 to October 2011 period and is aimed to capture the impact of the unrests in Tunisia that spread to Egypt and Libya, threatened Morocco, and created higher uncertainty when insurgencies and the calls for democracy in many other African countries were getting traction. Originated in Africa, the Ebola outbreak (EBC) is a health crisis which seriously damaged the overall African continent's reputation as an investment opportunity area (Del Giudice and Paltrinieri, 2017). The crisis stretches over 13 months, from May 2014 to May 2015. The Brexit (BXT) accounts for the uncertainty around the United Kingdom (UK) decision of withdrawal from the European Union. It runs over 10 months, from June 2016 with the UK referendum on continued EU membership, to March 2017. Finally, the Covid-19 pandemic (CVD) spans from February 2020 to December 2021.[7]

We estimate the following regression for each market and region to assess the changes in investors' herding behavior during these hard times:

[7] Although the COVID-19 pandemic is called off only in March 2023 by the World Health Organization, the panic/crisis subsided earlier, in December 2021, when vaccines were introduced.

$$h_{Mt} = \alpha + \sum_{k=1}^{K} \mathrm{b}_k D_{k,t} + \xi_t \quad (9)$$

where h_{Mt} is the herding measure estimates obtained from Model 2; $D_{k,t}$ is a dummy variable taking the value of 1 in the months of the crisis k, and 0 otherwise, with k=1 to 5 respectively for EDC, ASC, EBC, BXT, and CVD. We separately investigate and contrast the herding behavior of investors during periods of health crises (HTH) comprising the Ebola outbreak and the Covid-19 pandemic, and periods of political crises (POL) encompassing the Brexit and the Arab Spring uprising. Similarly, the impact of internally originated crises (ASC, EBC, and CVD) is contrasted with the impact of external crises (EDC and BXT which are mainly European originated). The regression is estimated via GMM while using the approach of Newey and West (1987) to adjust for the autocorrelations in the residuals, ξ_t. The slope coefficients, b_k, are reported in Table 4, along with the robust GMM-based t-statistics in parentheses.

TABLE 4 ABOUT HERE

The intercept (α), representing the average herding measure over the entire sample period, consistently shows a negative value significantly different from zero. This provides evidence of adverse herding behavior after controlling for the effects of the five crises (as shown in Panel A of Table 4), across all markets except Ghana, which exhibits significant regular herding, and notably for Mauritius and South Africa with no herding. Although statistically significant, the average herding measures are quite small, ranging from -0.008 for Egypt to -0.129 for the group of Most Frontier markets. Consequently, the baseline adverse herding behavior appears to be negligible.

While the EDC had a significant impact on investor herding behavior in Egypt and Morocco, and to some extent in Kenya, South Africa, and the Most Frontier markets, the

ASC, the EBC, and the BXT did not significantly alter investor herding behavior in the three North African markets, despite the entire region being affected primarily by the Arab Spring crisis. The ASC did influence herding in Ghana, as well as in Kenya, Nigeria, South Africa, and the Most Frontier markets. Meanwhile, the EBC notably impacted investor herding behavior in Cote d'Ivoire, Kenya, Nigeria, and the Most Frontier countries. Interestingly, the global COVID-19 pandemic did not directly lead to herding behavior, but significantly accelerate adverse herding among investors in Egypt, Botswana, South Africa, and the Most Frontier markets. This finding aligns with the conclusions of Kunjal and Peerblai (2021), who suggested that the COVID-19 pandemic led to adverse herding in South Africa.

In Panel B of Table 4, we present the findings regarding the influence of health crises versus political crises on investor herding behavior. Notably, health crises had a significant impact on the herding measure in Egypt, Morocco, and South Africa. However, only political crises exhibited significant effects on herding behavior in Tunisia, Côte d'Ivoire, Ghana, Nigeria, and South Africa.

Finally, we conduct a separate analysis to assess the effects of both internal crises (ASC, EBO, CVD) and external crises (EDC and BXT), with the later primarily emanating from Europe. The findings presented in the last columns (Panel C) of Table 4 reveal that external crises induced regular herding in Egypt, Cote d’Ivoire, Nigeria, South Africa, as well as in the Most Frontier markets. Interestingly, internally originated crises did not lead to more herding in any of the African country but Morocco, compared to external crises. At the regional level, the Sub-Saharan and the North African markets are subject to more regular or positive herding in periods of external crises, and more adverse herding in periods of internal crises.

4.3. Positive and adverse herding over time

The use of a significant σ_η as an indication of the existence of herding in the previous sub-section hides the true nature of the herding behavior, whether it is a regular herding or an adverse herding. To gain a better understanding of investors' behavior, we examine the dynamic of the herding measure extracted from the state-space model in each market and region. The measure $h_{Mt} = 1 - \exp(H_{Mt})$ is used to identify periods of extreme degree of herding (h_{Mt} close to 1), as well as cycles of regular ($h_{Mt} > 0$) and adverse herding ($h_{Mt} < 0$). A positive herding towards the market portfolio promotes a convergence of assets' betas toward the market portfolio beta, while an adverse herding indicates a divergence of asset's beta from the market portfolio beta.[8]

Figure 1 illustrates the evolution of the herding measure in the whole African market, as well as in each country and the Most Frontier markets.

FIGURE 1 ABOUT HERE

The figures reveal episodes of adverse or negative herding leading to an increase in the dispersion of individual betas. However, the episodes of sudden and more pronounced adverse herding caused by under-confidence in the market are short-lived phenomenon and

[8] If the true beta of a typical asset is higher than the market beta, this asset will have a beta less than its true beta in periods of positive herding, and a beta higher than its true beta in periods of adverse herding. Conversely, if the true beta of the asset is lower than the market beta, it will have a beta greater than its true beta in period of positive herding, and a beta lower than its true beta in periods of adverse herding.

are largely related to periods of crisis. Adverse herding behavior reflects strong self-confidence of investors and their mistrust against each other. As illustrated by the case of All African countries, investor behavior in many African countries alternate between periods of no herding (h_{Mt} close to zero) to adverse herding (h_{Mt} <0) which intensifies in times of crisis. The intensification of the adverse herding behavior occurs early in some crisis period such as the EDC and the ASC periods, and in the mid to late stages of BXT and CVD periods, mirroring the severity of each crisis or how it unfolds. These results are consistent with those of Xing, Cheng and Sun (2024) in Chinese A-Share market, and Yang and Chuang (2023) who find that anti-herding is prevalent in recent years and that herding is slight even in the COVID 19 pandemic period in Taiwan, China and the U.S. markets.

Figure 1 also reveals the diverse patterns of investor herding behavior across different countries. It's noteworthy that in Egypt and Ghana, the herding measure predominantly hovered around zero (indicating no herding), except for a single distinct event in each country: The Arab Spring crisis in Egypt triggered a market-oriented herding among investors, and a similar trend was observed in Ghana during a local economic crisis in 2022, which prompted regular herding behavior among investors. Ghana grappled with a significant economic crisis characterized by a default on most of its foreign debts, rampant inflation, and a precarious financial situation with a severe depreciation of its local currency in 2022. These economic challenges were further compounded by the delaying effects of the COVID-19 pandemic. This period of intense local crisis witnessed extreme investor herding behavior in the Ghanaian stock market.

The herding measure remained close to zero (indicating no herding) in Nigeria for almost the entire sample period. In contrast, the Most Frontier markets exhibited considerable fluctuations in investor herding behavior: while regular herding appeared to be the norm in the early years of our sample period, adverse herding has been the dominant trend since late 2018 in the Most Frontier markets.

5. Conclusion

This paper addresses two critical questions: First, do investors exhibit herding behavior in African stock markets? Second, how do major crises impact investor herding behavior in these markets? Herding, which can affect liquidity, increase volatility, and influence price convergence, warrants close examination for the development of efficient stock markets in Africa.

Departing from previous static analyses, our study employs a state-space model to investigate the dynamic nature of herding over time in 17 African stock markets between 2009 and 2022, with a focus on the five main crises during that period. Our findings reveal a pattern of alternating periods: some with minimal or no herding, and others marked by persistence adverse herding. Notably, crisis periods exhibit short-lived, pronounced episodes of adverse herding, with external crises having a more significant impact than internal ones across African markets.

Given that Africa hosts several stock exchanges aimed at bolstering economic development, and the culture of stock market participation is still evolving, a critical question is how to enhance these exchanges' competitiveness and efficiency to increase investor confidence and capital inflow. Consequently, our findings hold significant implications for market participants, including international investors, market regulators, and policymakers. Especially, policymakers should carefully consider these insights when designing interventions to promote market stability and resilience. Additionally, the implementation of regulatory measures to oversee and alleviate potential risks linked to herding behavior is of utmost importance, especially in times of crisis or economic hardship.

Further analysis and research may be warranted to explore the underlying drivers of adverse herding behavior in African equity markets. Investigating factors such as investor sentiment, information asymmetry, market structure, and institutional characteristics could provide deeper insights into the dynamics of herding and its consequences.

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Table 1. Evolution of the sample of stocks.

Country	Total	Per year													
		2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Egypt	254	181	187	190	197	211	214	224	232	234	240	241	242	248	249
Morocco	77	59	62	65	66	67	68	70	71	71	73	73	74	75	77
Tunisia	80	44	46	52	53	62	71	73	74	76	77	77	78	79	80
North Africa	*411*	*284*	*295*	*307*	*316*	*340*	*353*	*367*	*377*	*381*	*390*	*391*	*394*	*402*	*406*
Botswana	27	14	15	17	18	19	19	20	22	24	25	26	26	26	27
Cote d'Ivoire	41	33	34	35	35	35	35	35	37	39	40	39	39	39	40
Ghana	37	28	28	28	28	28	28	32	32	34	36	36	36	37	37
Kenya	74	54	54	60	60	64	64	67	68	66	63	67	67	64	63
Malawi	13		5	10	10	10	10	10	10	10	10	11	13	13	13
Mauritius	86	57	58	59	61	61	64	67	72	73	76	79	81	83	83
Namibia	3											2	2	3	3
Nigeria	183	148	162	162	162	164	168	170	171	173	145	141	165	160	171
Rwanda	6			2	2	2	2	2	2	3	4	4	4	5	6
South Africa	253	181	183	191	193	199	213	222	227	238	242	246	248	249	250
Tanzania	21	7	10	10	9	10	12	14	11	16	14	13	12	13	16
Uganda	11	6	7	7	7	7	7	9	7	7	8	8	6	6	8
Zambia	21			17	17	17	18	18	19	20	20	20	21	21	21
Zimbabwe	54	46	47	47	47	47	45	46	46	48	50	52	52	52	54
Most Frontier	*129*		*59*	*69*	*93*	*92*	*93*	*94*	*99*	*95*	*104*	*106*	*110*	*110*	*113*
Sub-Sahara	*830*	*574*	*603*	*645*	*649*	*663*	*685*	*712*	*724*	*751*	*733*	*744*	*772*	*771*	*792*
All Africa	1,241	858	898	952	965	1,003	1,038	1,079	1,101	1,132	1,123	1,135	1,166	1,173	1,198

The column labelled "Total" gives the total number of stocks used for each country. The remaining 14 columns show the yearly evolution of the number of stocks in each country from 2009 to 2022. We classify the countries into three North African countries (Egypt, Morocco, and Tunisia) and fourteen Sub-Saharan countries (Botswana, Cote d'Ivoire, Ghana, Kenya, Malawi, Mauritius, Namibia, Nigeria, Rwanda, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe). Because they have low coverage, seven Sub-Saharan markets (Malawi, Namibia, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe) are grouped into a "Most Frontier" category. The data are from Datastream.

Table 2. Descriptive statistics.

Country	Market capitalization		Market return			CSDB				
	Size	Weight	Mean	SD1	SD2	Mean	SD	Skewness	Kurtosis	JB
Egypt	41,401	5.702	1.174	7.604	7.241	0.747	0.244	0.352	0.724	7.136*
Morocco	53,672	7.393	0.580	4.191	2.893	0.959	0.319	0.924	1.399	37.58*
Tunisia	6,979	0.961	0.400	3.876	2.804	0.760	0.275	1.127	2.499	79.270*
North Africa	*102,052*	14.056	*0.750*	*4.460*	*4.340*	*1.218*	*0.299*	*1.224*	*2.086*	*72.423**
Botswana	3,584	0.494	0.555	3.803	3.486	0.565	0.413	1.462	1.907	84.298*
Cote d'Ivoire	8,471	1.167	4.255	17.630	13.075	0.536	0.255	0.063	0.443	1.300
Ghana	2,393	0.330	1.151	9.703	6.993	1.018	0.662	0.960	1.116	33.682*
Kenya	17,099	2.355	1.383	6.877	3.440	1.210	0.366	0.287	0.829	7.111*
Mauritius	67,528	9.301	0.740	5.675	3.915	0.833	0.352	1.464	5.104	242.387*
Nigeria	47,907	6.599	1.895	14.281	10.328	0.874	0.334	0.238	0.551	3.621
South Africa	467,198	64.350	1.288	7.178	6.157	0.681	0.182	1.104	2.164	66.940*
Most Frontier	9,792	1.349	3.928	19.024	12.026	0.800	0.430	0.925	0.496	24.132*
Sub-Sahara	*623,972*	85.944	*1.310*	*6.540*	*3.828*	*1.340*	*0.292*	*0.664*	*0.993*	*19.236**
All Africa	*726,024*	*100.000*	*1.170*	*5.840*	*3.220*	*1.518*	*0.370*	*0.602*	*0.224*	*10.502**

This table reports summary descriptive statistics for the African markets. The first two columns show the size (in millions of USD) and weight (in percent) of each market at the end of the coverage (in December 2022). The next three columns present the mean and standard deviation associated with the returns of each market. The column labelled "mean" gives the continuously compounded monthly average value-weighted market return, while "SD1" gives the associated standard deviation. "SD2" presents the root square of the monthly market variance, estimated from the sum of the squared daily returns (after subtracting the average daily return in the month). Finally, the last five columns report various statistics on the cross-sectional standard deviation of the betas (CSDB). The statistics presented are the mean, standard deviation, skewness, excess kurtosis, and Jarque–Bera (JB) statistics. All results are based on dollar-denominated daily returns from January 5, 2009, to December 31, 2022. We classify the countries into North African countries (Egypt, Morocco, and Tunisia) and Sub-Saharan countries (Botswana, Cote d'Ivoire, Ghana, Kenya, Mauritius, Nigeria, and South Africa). Because they have low coverage, seven Sub-Saharan markets (Malawi, Namibia, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe) are grouped into a "Most Frontier" category. For statistics on market returns and CSDB, the Most Frontier markets are not included in Sub-Sahara group. All data are from Datastream. * denotes significance at 5% level.

Table 3. State-space model estimation.

Country	A. Model 1						B. Model 2							
	μ	ϕ	σ_η	STN	ln(L)	BIC	μ	λ	γ	ϕ	σ_η	STN	*ln*(L)	BIC
Egypt	-0.372	0.190	0.539	0.984	-135.845	281.925	0.185	0.009	-0.336	0.055	0.509	0.930	-131.418	273.048
	(0.051)**	(0.076)**	(0.059)**				(0.155)	(0.005)	(0.087)**	(0.085)	(0.056)**			
Morocco	-0.101	0.599	0.268	0.813	-19.105	48.446	0.460	-0.005	-0.590	0.495	0.211	0.641	14.845	-19.479
	(0.051)*	(0.065)**	(0.029)**				(0.064)**	(0.004)	(0.058)**	(0.072)**	(0.023)**			
Tunisia	-0.343	0.460	0.321	0.899	-48.943	108.121	0.420	-0.008	-0.825	0.242	0.222	0.622	6.547	-2.883
	(0.046)**	(0.071)**	(0.035)**				(0.058)**	(0.005)	(0.058)**	(0.079)**	(0.024)**			
North Africa	0.168	0.547	0.193	0.842	35.908	-61.579	0.548	-0.006	-0.311	0.475	0.147	0.640	74.834	-139.456
	(0.032)**	(0.066)**	(0.021)**				(0.041)**	(0.003)*	(0.029)**	(0.071)**	(0.016)**			
Botswana	-0.817	0.153	0.704	0.990	-178.462	367.135	-0.944	0.004	0.115	0.147	0.706	0.994	-182.417	375.022
	(0.064)**	(0.078)*	(0.078)**				(0.179)**	(0.014)	(0.153)	(0.079)	(0.078)**			
Cote d'Ivoire	-0.597	0.297	0.407	0.956	-67.863	145.398	1.038	0.001	-0.770	0.173	0.370	0.869	-61.144	131.928
	(0.051)**	(0.086)**	(0.051)**				(0.300)**	(0.003)	(0.141)**	(0.089)	(0.047)**			
Ghana	-0.406	0.093	2.912	0.997	-400.504	811.159	-0.174	0.005	-0.149	0.087	2.929	1.003	-403.232	816.589
	(0.252)	(0.079)	(0.326)**				(0.696)	(0.024)	(0.403)	(0.082)	(0.329)**			
Kenya	0.137	0.560	0.279	0.837	-26.006	62.248	0.708	0.005	-0.520	0.609	0.217	0.650	10.011	-9.810
	(0.049)**	(0.066)**	(0.031)**				(0.069)**	(0.002)*	(0.049)**	(0.066)**	(0.024)**			
Mauritius	-0.266	0.284	0.399	0.961	-85.871	181.979	0.094	0.012	-0.313	0.220	0.377	0.908	-81.066	172.344
	(0.043)**	(0.075)**	(0.044)**				(0.097)	(0.005)*	(0.076)**	(0.078)**	(0.042)**			
Nigeria	-0.186	0.148	0.382	0.992	-75.297	160.744	0.911	0.002	-0.564	0.109	0.314	0.814	-50.089	110.302
	(0.035)**	(0.080)	(0.043)**				(0.128)**	(0.002)	(0.064)**	(0.083)	(0.035)**			
South Africa	-0.419	0.412	0.233	0.917	4.351	1.534	0.628	0.001	-0.617	0.579	0.222	0.648	55.516	-100.820
	(0.030)**	(0.071)**	(0.025)**				(0.085)**	(0.002)	(0.047)**	(0.067)**	(0.024)**			
Most Frontier	-0.354	0.579	0.455	0.818	-106.253	222.719	-0.033	0.001	-0.155	0.543	0.452	0.812	-110.985	232.157
	(0.083)**	(0.064)**	(0.050)**				(0.165)	(0.003)	(0.070)**	(0.067)**	(0.050)**			

Table 3 – *Continued*

Country	A. Model 1						B. Model 2							
	μ	ϕ	σ_η	STN	ln(L)	BIC	μ	λ	γ	ϕ	σ_η	STN	ln(L)	BIC
Sub-Sahara	0.266	0.510	0.188	0.869	40.387	-70.539	0.795	-0.001	-0.437	0.447	0.138	0.640	84.271	-158.330
	(0.029)**	(0.069)**	(0.021)**				(0.048)**	(0.001)	(0.036)**	(0.070)**	(0.015)**			
All Africa	0.384	0.592	0.198	0.817	31.762	-53.288	0.791	-0.004	-0.395	0.445	0.157	0.649	63.258	-116.304
	(0.037)**	(0.064)**	(0.022)**				(0.045)**	(0.001)*	(0.038)**	(0.074)**	(0.017)**			

The table reports the parameter estimates of the following state-space system for herding towards the market portfolio:

$$\text{(Model 2)} \qquad \log CSDB_t = \mu + H_{Mt} + \lambda R_{Mt} + \gamma \log(\sigma_{Mt}) + \upsilon_{Mt}, \tag{8}$$

$$H_{Mt} = \log 1 - h_{Mt} = \phi_M H_{Mt-1} + \eta_{Mt}, \tag{9}$$

where $CSDB_t$ is the monthly cross-sectional standard deviation of betas calculated using the OLS estimation of the market model of daily returns within each month, μ, λ, γ, and ϕ are the parameters estimated by maximum likelihood using the diffuse Kalman filter algorithm, υ_{Mt} is the observation noise, $\sigma_{M\eta}$ is the standard deviation of the state equation residual term (η_{Mt}), and STN is the signal-to-noise ratio computed by dividing σ_η by the time-series standard deviation of log $CSDB_t$. Below each parameter estimate, we report the associated standard error. We present in Panel A the results from the estimation of the restricted version of the system without the market return (R_{Mt}) and the logarithm of the market's standard deviation ($\log(\sigma_{Mt})$), which we call Model 1, and in Panel B the results from the unrestricted system (Model 2). The last two columns give the Maximum likelihood values and the Schwarz information criterion or Bayesian information criterion (BIC). All results are based on dollar-denominated daily returns from January 5, 2009, to December 31, 2022. We classify the countries into North African countries (Egypt, Morocco, and Tunisia) and Sub-Saharan countries (Botswana, Cote d'Ivoire, Ghana, Kenya, Mauritius, Nigeria, and South Africa). Because they have low coverage, seven Sub-Saharan markets (Malawi, Namibia, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe) are grouped into a "Most Frontier" category. All data are from Datastream. * and ** represent significance at 5% and 1% levels, respectively.

Table 4. Herding during hard times.

Country	A. All Crises						B. Health and Political Crises			C. Internal and External Crises		
	α	b_{EDC}	b_{ASC}	b_{EBC}	b_{BXT}	b_{CVD}	α	b_{HTH}	b_{POL}	α	b_{INT}	b_{EXT}
Egypt	-0.008	0.010	0.025	0.002	0.009	-0.009	-0.006	-0.006	0.016	-0.008	0.001	0.009
	(-3.73)**	(4.13)**	(1.32)	(0.37)	(0.83)	(-3.40)**	(-3.44)**	(-2.15)**	(1.38)	(-3.73)**	(0.25)	(1.92)*
Morocco	-0.064	0.064	0.018	0.028	-0.025	0.096	-0.056	0.065	-0.010	-0.064	0.060	0.028
	(-4.41)**	(2.10)**	(0.58)	(1.13)	(-0.56)	(3.24)**	(-4.12)**	(2.58)**	(-0.34)	(-4.41)**	(2.56)**	(0.91)
Tunisia	-0.013	-0.018	0.017	-0.004	0.021	-0.001	-0.015	0.000	0.021	-0.013	0.002	-0.002
	(-2.10)**	(-1.39)	(1.07)	(-0.24)	(1.32)	(-0.09)	(-2.67)**	(-0.01)	(1.76)*	(-2.10)**	(0.19)	(-0.19)
North Africa	-0.045	0.063	0.045	-0.001	0.050	-0.033	-0.038	-0.029	0.040	-0.045	-0.007	0.058
	(-5.30)**	(3.08)**	(2.23)**	(-0.04)	(1.81)*	(-1.72)*	(-4.4)**	(-1.61)	(2.24)**	(-5.30)**	(-0.39)	(3.29)**
Botswana	-0.022	0.022	0.006	0.002	0.035	-0.041	-0.020	-0.029	0.017	-0.022	-0.019	0.027
	(-1.90)*	(1.03)	(0.24)	(0.04)	(1.17)	(-1.99)**	(-1.87)*	(-1.34)	(0.80)	(-1.90)*	(-0.96)	(1.39)
Cote d'Ivoire	-0.026	-	-	0.024	0.020	0.004	-0.026	0.011	0.020	-0.026	0.011	0.020
	(-3.49)**			(1.76)*	(2.23)**	(0.34)	(-3.49)**	(1.00)	(2.23)**	(-3.49)**	(1.00)	(2.23)**
Ghana	0.024	-0.022	-0.058	-0.003	-0.017	-0.017	0.021	-0.009	-0.036	0.024	-0.023	-0.020
	(1.78)*	(-1.47)	(-3.43)**	(-0.10)	(-0.66)	(-1.06)	(1.79)*	(-0.61)	(-1.99)**	(1.78)*	(-1.39)	(-1.21)
Kenya	-0.094	0.079	0.116	-0.082	-0.070	-0.006	-0.084	-0.042	0.019	-0.094	0.001	0.018
	(-5.15)**	(1.72)*	(5.70)**	(-3.17)**	(-1.60)	(-0.15)	(-4.86)**	(-1.36)	(0.42)	(-5.15)**	(0.04)	(0.41)
Mauritius	0.003	0.004	-0.010	-0.014	-0.025	-0.024	0.003	-0.021	-0.018	0.003	-0.018	-0.008
	(0.26)	(0.23)	(-0.67)	(-0.79)	(-1.04)	(-1.50)	(0.34)	(-1.61)	(-1.19)	(0.26)	(-1.41)	(-0.45)
Nigeria	-0.013	0.010	0.015	0.025	0.019	-0.008	-0.012	0.003	0.016	-0.013	0.006	0.013
	(-3.27)**	(1.45)	(2.03)**	(3.52)**	(2.99)**	(-0.98)	(-3.28)**	(0.33)	(2.91)**	(-3.27)**	(0.93)	(2.40)**
South Africa	-0.011	0.037	0.098	-0.005	0.092	-0.145	-0.007	-0.100	0.091	-0.011	-0.052	0.060
	(-0.80)	(1.66)*	(6.29)**	(-0.18)	(4.09)**	(-2.83)**	(-0.53)	(-2.51)**	(5.86)**	(-0.80)	(-1.36)	(2.78)**
Most Frontier	-0.129	0.151	0.335	0.266	0.052	-0.282	-0.111	-0.107	0.183	-0.129	0.007	0.111
	(-3.04)**	(2.60)**	(6.51)**	(4.95)**	(0.98)	(-3.26)**	(-2.87)**	(-1.10)	(2.65)**	(-3.04)**	(0.08)	(2.07)**

Table 4 – *Continued*

Country	A. All Crises						B. Health and Political Crises			C. Internal and External Crises		
	α	b_{EDC}	b_{ASC}	b_{EBC}	b_{BXT}	b_{CVD}	α	b_{HTH}	b_{POL}	α	b_{INT}	b_{EXT}
Sub-Sahara	-0,019	0,009	0,029	0,007	0,059	-0,082	-0,018	-0,052	0,042	-0,019	-0,032	0,029
	(-2,86)**	(0,67)	(1,44)	(0,29)	(3,38)**	(-5,44)**	(-2,95)**	(-2,85)**	(2,85)**	(-2,86)**	(-1,88)*	(2,11)**
All Africa	-0,034	0,020	0,028	0,005	0,040	-0,050	-0,032	-0,033	0,032	-0,034	-0,017	0,028
	(-4,25)**	(0,90)	(0,86)	(0,19)	(1,12)	(-3,68)**	(-4,17)**	(-2,13)**	(1,28)	(-4,25)**	(-1,08)	(1,38)

The table reports the parameter estimates of the following equation:

$$h_{Mt} = \mathrm{a} + \sum_{k=1}^{K} \mathrm{b}_k D_{k,t} + \xi_t \qquad (9)$$

where h_{Mt} is the herding measure estimates obtained from Model 2; $D_{k,t}$ is a dummy variable taking the value of 1 in the months of the crisis k, and 0 otherwise, with k=1 to 5 respectively for the Eurozone sovereign debt crisis (EDC), the Arab Spring crisis (ASC), the Ebola crisis (EBC), the Brexit (BXT), and the Covid-19 pandemic (CVD). $D_{k,t}$ also takes the value of 1 in the month of (i) health crises (HTH) comprising the Ebola outbreak and the Covid-19 pandemic, (ii) political crises (POL) covering the Brexit and the Arab Spring uprising, (iii) internal crises (ASC, EBC, CVD), and (iv) external crises (EDC, BXT). The regression is estimated via GMM while using the approach of Newey and West (1987) to adjust for the autocorrelations in the residuals, ξ_t. We classify the countries into North African countries (Egypt, Morocco, and Tunisia) and Sub-Saharan countries (Botswana, Cote d'Ivoire, Ghana, Kenya, Mauritius, Nigeria, and South Africa). Seven other Sub-Saharan markets (Malawi, Namibia, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe) are grouped into a "Most Frontier" category. Data are from January 2009 to December 2022. The robust GMM-based t-statistics are in parentheses. * and ** represent significance at 5% and 1% levels, respectively.

Figure 1. Dynamic of market herding.

The figure shows the time series of h_{Mt}, the herding measure obtained from Model 2, over the sample period. It highlights the crisis periods (Eurozone sovereign debt crisis, Arab Spring crisis, Ebola crisis, Brexit, and the Covid-19 pandemic, chronologically).

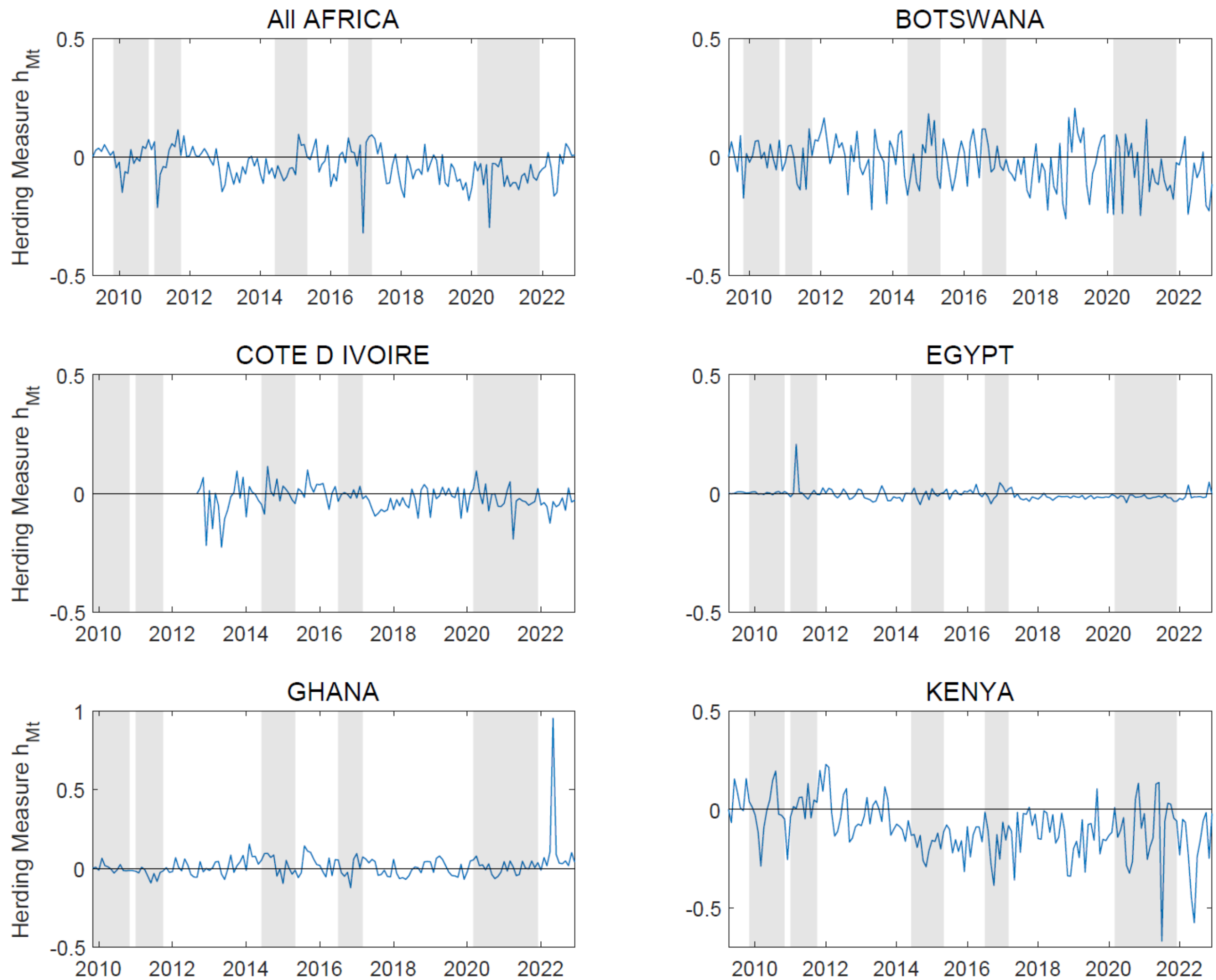

Figure 1. (*Continued*)