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Investor herds and regime-switching: Evidence from Gulf Arab stock markets

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ABSTRACT

This paper proposes a dynamic herding approach which takes into account herding under different market regimes, with concentration on the Gulf Arab stock markets – Abu Dhabi, Dubai, Kuwait, Qatar and Saudi Arabia. Our results support the presence of three market regimes (low, high and extreme or crash volatility) in those markets with the transition order 'low, crash and high volatility', suggesting that these frontier markets have a different structure than developed markets. The results also yield evidence of herding behavior under the crash regime for all of the markets except Qatar which herds under the high volatility regime. The findings of the cross-GCC herding model also demonstrate herding comovements and not spillovers and are also robust to the cross-GCC volatility shocks. The tests that underline the cross-volatility shocks suggest that the crash regime is a true regime and not a statistical artifact. Policy and portfolio diversification implications are discussed.

1. Introduction

Herding behavior in financial markets has attracted increasing attention over the past decade. The literature defines herding as an obvious intent by investors to ignore their personal beliefs (or information) and copy the behavior of other investors (Bikhchandani and Sharma, 2001), leading them to trade in the same direction and thus moving in and out of markets as a group (Nofsinger

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and Sias, 1999). Even though such behavior among investors can be driven by rational or irrational motives, it can clearly lead to market stress by pushing asset prices away from their fair values as supported by the economic fundamentals, hence driving up market volatility (Blasco et al., 2012). Most of the herding literature concentrates on developed markets, while other studies focus on prominent emerging markets. This study considers frontier markets.

The first contribution of this paper is to extend the literature on investor herds to frontier stock markets in the Gulf Cooperation Council (GCC) countries – namely UAE (Abu Dhabi and Dubai), Kuwait, Qatar and Saudi Arabia – which can be highly sensitive to herding for reasons indicated below. The second and main contribution is to propose a modification to the standard herding approach employed in prior studies, and utilize a new herding model that takes into account herding under different market regimes, with concentration on these oil-rich countries. For this purpose and as warranted by the data, we estimate a three-state Markov-switching (MS) model for the cross-sectional dispersions of stock returns in the five GCC stock markets, and examine the relationships between their market returns and return dispersions during different market regimes. Unlike the standard herding methodology available in the literature, this alternative specification allows us to differentiate between different market states when herding behavior may or may not exist. Thus, our paper has three novelties. There are three-regimes suggested by the data, with the third one specifying herding under a crash. All parameters of the model are allowed to vary across regimes and not only the variance. Finally, the MS specification fully allows regime-specific volatilities by specifying regime-dependent heteroscedasticity.

There are multiple reasons that make examining herding behavior in the GCC stock markets of particular interest. First, the economies of the GCC countries are highly sensitive to oil prices and propped by oil revenues.[1] Therefore, the developments in the global oil market, either in the form of rumors or facts, can potentially generate herding behavior in the GCC stock markets. Second, GCC stock markets are classified as frontier markets due to a number of market and institutional issues including liquidity, lack of effectiveness of their delivery versus payment settlement system, ownership limits on foreign investments, etc. Therefore, regional more than global shocks such as the shocks in their real estate markets can push investors to the railing. Third, regional geopolitical factors can also create additional uncertainty regarding the performance of these markets and may trigger the fear instinct among investors, potentially leading to herding behavior where investors are likely to copy the behavior of others. Fourth, the GCC countries are connected through a political and economic union, so a market shock in one member country can be quickly transmitted to the other members, institutionalizing herding mentality. In these markets, misinformation or lack of information would deprive GCC investors from the privilege of resorting to the fundamental analysis to make sound market decisions, thus providing individual investors with incentives to simply go with the market consensus. Finally, the major GCC countries like Saudi Arabia and UAE possess large amounts of money but they suffer from limited investment opportunities and under-populated stock exchanges which can be characterized by the phenomenon "too much money chasing too few stocks". Therefore, the lack of sufficient investment opportunities in these markets that are flushed with cash, coupled with a lack of investment culture among retail investors which dominate the GCC markets, can further feed into herding tendencies in these markets. For these reasons, it would be interesting to study herding in markets where stocks are thinly traded and some prices may take several trading days to move. Furthermore, the fact that these GCC countries are classified as frontier markets and currently bidding to be upgraded to the emerging market status makes it even more interesting and valuable to examine herding behavior in these markets.[2]

Regarding possible motives for herding behavior among investors, a number of papers in the literature have provided explanations. However, one must note that these explanations have generally been applied to developed markets and may not fit very closely with a possible herding behavior in developing stock markets, including those in the GCC countries. One strand of literature including Shleifer and

[1] A prospective study that incorporates oil prices and other global factors will require the use of weekly data because of different trading days in the week between the GCC and world markets.

[2] All GCC markets are frontier markets which aspire to be upgraded to the emerging market status as defined by the index provider MSCI.

Summers (1990), Froot et al. (1992), Avery and Zemsky (1998) and Chari and Kehoe (2004) suggest that individual investors prefer to follow the actions of more informed traders believing that the actions of informed traders reveal useful information which may not be accessible to individual investors. On the other hand, studies including Banerjee (1992), Bikhchandani et al. (1992) and Shiller (2002) suggest that informational cascades, where investors' inferences on what other investors' actions might imply, create behavioral trends. Following an agency theory-based explanation, Scharfstein and Stein (1990), Rajan (1994), Maug and Naik (1996), Graham (1999), and Swank and Visser (2008) suggest that fund managers prefer to imitate others as a result of compensations schemes offered to them or in order to maintain their reputation.

Whatever the underlying motivation for herding behavior might be, herding however is not without its cost. In the case of GCC markets, herding has proven to be harmful to the uninformed investors. More specifically, the 1982 Kuwait stock exchange crash which followed strong herding that pulled stock prices away from their fair values, caused substantial damage to the Kuwaiti economy and investors. Similarly, the Saudi and Dubai markets crashed in 2006 and 2008 after equity prices wandered off their fundamentals, causing havoc on individual investors.

Our results suggest the presence of three market regimes (low, high and extreme or crash volatility regimes) in the uncommon order of 'low, crash, and high volatility' in the GCC stock markets. The regime-based tests yield significant evidence of herding behavior under the crash regime for all of the markets except Qatar which herds under the high volatility regime. Interestingly, the static herding model incorrectly rejects herding in Kuwait and Abu Dhabi while in fact these two markets display herding behavior during the crash regime only. The findings of the cross-GCC herding model support the presence of herding comovements and not spillovers and they are also robust to the cross-GCC volatility shocks. The tests that underline these shocks suggest that the crash regime is a true regime and not a statistical artifact.

An outline of the remainder of the paper is as follows. Section 2 briefly presents the literature on tests of investor herds and the standard dispersion-based testing methodology. Section 3 summarizes previous research on GCC markets, while Section 4 provides the description of the data and proposed testing methodology. Section 5 presents the empirical results for the standard and regime-based herding tests as well as evidence on cross-country herding effects. Finally, Section 6 concludes the paper and discusses implications of the findings.

2. Tests of herding behavior

Tests of herding behavior can be organized into two broad categories; the first category is based on trading data, i.e., buy and sell orders executed by traders in a given time frame,[3] and the other is based on returns of assets organized into groups of similar characteristics such as a country or sector classifications. Starting with Christie and Huang (1995) on U.S. equities, a number of studies in the literature have utilized a measure of cross-sectional dispersion of stock returns and examined the relationship between return dispersions and market return in order to make inferences on whether herding behavior exists. Later, the testing methodology by Christie and Huang (1995) was modified by Chang et al. (2000) and this modified methodology has been employed in a number of papers including Gleason et al. (2003) on commodity futures traded on European exchanges, Gleason et al. (2004) on exchange traded funds, Demirer and Kutan (2006) and Tan et al. (2008) on Chinese stocks, and more recently Demirer et al. (2010) on Taiwanese stocks and Chiang and Zheng (2010) on global stock markets.

The return dispersion-based testing methodology, suggested by Chang et al. (2000), employs the cross-sectional absolute deviation of returns (CSAD) as a measure of return dispersion formulated as

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

[3] See for example Lakonishok et al. (1992).

where N is the number of stocks in the portfolio, $R_{i,t}$ is the observed return on stock i on day t and $R_{m,t}$ is the return on the market on day t. From a rational, efficient market perspective, one would expect the dispersion across security returns to be positively related to the size of market return shocks as securities would have different sensitivities to the market return. Considering a single factor model where systematic risk is measured by a security's beta, the cross-sectional variation in security betas is expected to lead to greater cross-sectional return dispersion for greater values of absolute market return. However, in a market where herding behavior is prevalent, investors' correlated actions of moving in and out of particular sectors or stocks might break the positive and linear relationship between return dispersion and market return. If in fact herding behavior exists, one can then argue that correlated actions of investors would lead stock returns to exhibit greater cross-sectional similarity, giving rise to lower dispersion more prevalently during periods of market stress. Therefore, the testing methodology examines the relationship between return dispersions and market returns during periods of large market movements and estimates the following model:

$$CSAD_t = \alpha + \alpha_1 \left| R_{m,t} \right| + \alpha_2 R_{m,t}^2 + \varepsilon_t \tag{2}$$

where $R_{m,t}$ is the return on the market on day t. Based on the conditional CAPM, one would expect the cross-sectional variation in stock betas to lead to a positive estimate for α_1 as stocks would react differently to market return shocks. However, a significant value for α_2 would suggest that the theoretical linear relationship breaks down for large returns. Furthermore, observing a negative and significant value for α_2 would further suggest greater directional similarity in stock returns during periods of market stress, and thus is used in this methodology as a support for herding behavior.

However, a major weakness of this methodology is that it is based on a static specification where the model parameters are assumed to be constant over time. In other words, the static model of Eq. (2) ignores possible structural breaks and regime changes that may create varying states of uncertainty in a regime-changing environment, and thus may impact herding behavior. Considering that herding behavior would be more prevalent during periods of market stress[4] and in a regime-changing environment, one would suggest a warranted approach of time-varying herding behavior that is able to differentiate between the different market states where herding behavior may or may not exist. Therefore, it would be interesting and valuable to examine herding behavior under regime switching and apply it to the frontier markets of GCC countries which have relatively unique market characteristics. To our best knowledge, the only study in the literature that examines herding behavior in GCC markets is Demirer and Ulussever (2011). However, that study is based on the static model described earlier and does not address time-varying herding under different market regimes. In this study, we fill a gap in the herding literature by formally testing whether the static model adequately captures herding behavior in the frontier GCC markets, and compare the findings with a regime-based herding model that accommodates multiple regimes.

3. Previous studies on GCC markets

The first stream of the GCC stock market literature examines market return interdependence using the linear VEC model. Assaf (2003) examines the dynamic interdependence among the six GCC markets using the linear VEC model for the weekly sample period January 15, 1997 to April 26, 2000. His findings suggest interdependence among these markets. Specifically, he finds Bahrain, which has a relatively more open market, leading other GCC markets, while Saudi Arabia's more segmented and closed market lagging in receiving shocks from the other markets. On the other hand, Hammoudeh and Aleisa (2004), also using linear VEC models for the daily period February 25, 1994 to December 25, 2001, find that Saudi Arabia plays the leading role in moving other GCC markets, without being responsive to their shocks. Their findings also underline the reaction of these markets to movements of the NYMEX 3-month futures WTI price, showing that only Saudi Arabia has a bidirectional relationship with this oil price. Hammoudeh and Li (2008) examine the sudden changes in volatility for five Gulf markets, using the iterated cumulative sums of squares (ICSS) algorithm, and analyze their impacts on

[4] See, for example, Christie and Huang (1995).

Table 1
Descriptive statistics.

	Saudi Arabia	Kuwait	Dubai	Abu Dhabi	Qatar
Panel A: R_m					
Mean	−0.08%	−0.04%	−0.13%	−0.04%	0.01%
Std. dev.	1.58%	0.84%	2.11%	1.34%	1.74%
Min.	−10.33%	−3.80%	−11.34%	−8.50%	−8.93%
Max.	9.05%	3.88%	12.82%	11.01%	9.88%
Panel B: *CSAD*					
Mean	1.54%	1.71%	1.70%	2.39%	1.51%
Std. dev.	0.89%	1.23%	2.62%	2.24%	1.02%
Min.	0.46%	0.62%	0.12%	0.42%	0.34%
Max.	6.23%	34.30%	61.07%	24.44%	21.00%

Notes: Panels A and B report the descriptive statistics for daily market index returns and cross-sectional return dispersions across all listed stocks in each exchange as formulated in Eq. (1), respectively. CSAD is the cross-sectional absolute deviation of returns as a measure of return dispersion. The sample period covers from 7/9/2006 to 9/28/2011 with a total number of 993 observations for each country.

volatility persistence. They find that most of the Gulf Arab stock markets are more sensitive to major global events than to local and regional factors. Their results support the finding which asserts the impacts of the 1997 Asian crisis, the collapse of oil prices in 1998 after the crisis, the adoption of the oil price band mechanism by OPEC in 2000 and the 9/11 attack on New York on the GCC markets. This finding is surprising because GCC markets are frontier markets in which regional factors dominate global factors.

More recently, Marashdeh and Shrestha (2010), employing the autoregressive distributed lag (ARDL) approach to cointegration, find that the GCC markets are not fully integrated and that these markets are not integrated with the developed markets as represented by the United States and European markets. These findings imply that there is a more profitable opportunity of portfolio diversification between the GCC and the developed countries than between the more integrated GCC markets. Ravichandran and Maloain (2010) use the error-composition model to examine how a financial crisis may affect the long-run relationship and the short-run linkages among GCC stock markets. The empirical evidence indicates that the long- and short-run relationships among these markets strengthen, and the markets become more integrated regionally and globally after a crisis than before it.

The Markov-switching literature on the GCC markets is limited and, to our knowledge, does not address herding. Employing the univariate GARCH approach with Markov-switching, Hammoudeh and Choi (2007) decompose the stock returns of the GCC stock markets into permanent and transitory components in order to measure the switch in volatility between the high and low variance regimes for the GCC countries. They compare the conditional volatility and correlations between the individual GCC stock markets and with the oil price and the stock market of the oil-exporting Mexico. Their estimates suggest that the low and high volatility regimes are statistically significant for all the GCC stock markets. Finally, Balcilar and Genc (2010) examine the dynamic links between crude oil prices and six GCC stock market indices, using a four regime Markov-switching vector autoregressive (MS-VAR) model and weekly data over the period 1994–2010. They find that there are no lead and lag relationships between crude oil prices and any of the GCC stock markets. They, however, find that oil prices are informative in predicting the regime of the GCC stock markets.

4. Data and methodology

4.1. Data

The dataset consists of daily closing prices for individual stocks listed on six GCC stock exchanges including those for Saudi Arabia, Dubai, Abu Dhabi, Kuwait, and Qatar obtained from Reuters. The data covers the period from 07/09/2006 to 09/28/2011, with a total number of 993 observations for each country. Table 1 provides summary statistics for the daily market index returns and cross-sectional return dispersions. Examining the market index returns reported in Panel A, we observe that Dubai is the most volatile market while Kuwait has the lowest volatility. Dubai's high volatility is most likely due to the fast growth in its real estate and construction sectors during much of the 2000s, fueled particularly by borrowing and the influx of borrowed petrodollars. Another reason for the high volatility observed in Dubai may be due to the debt crisis experienced in this emirate for the last few years. However, we observe negative average returns in all markets except Qatar. This is most likely due to the two major market crashes (credit and real estate markets) these markets experienced in the last decade on one hand, and increases in natural gas exports and interventions in the market by the government in Qatar on the other hand.

In the case of return dispersions (reported in Panel B), the stock market in Abu Dhabi has the highest mean value, suggesting higher variations across stock returns in this market compared to other GCC countries. This may also suggest that the stock return in Abu Dhabi had unusual cross-sectional variations due to unexpected news or shocks which, again, can be due to the strong oil boom and the subsequent crashes in oil prices and the real estate market. It is also possible that the unusually high return dispersion in Abu Dhabi is to due to the dual diversity of companies and investors in this market.

4.2. Testing herding behavior under regime switching

In order to capture the dynamic nature of the relationship between return dispersions and market returns, we differentiate between the different market states where herding behavior may or may not exist in one or another of these states. For this purpose, we estimate the following three-state Markov switching model of the cross-sectional return dispersions:

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{mt}\right| + \alpha_{2,S_t}R_{mt}^2 + \varepsilon_t \quad (3)$$

where $\varepsilon_t \sim iid(0, \sigma^2_{St})$ and S_t is a discrete regime variable taking values in {0,1,2} and following a three-state Markov process. Thus, the random variable S_t is defined as a 3-state first order Markov chain. The specification is completed by defining the transition probabilities of the Markov chain as $p_{ij} = P(S_{t+1}|S_t = j)$. Thus, p_{ij} is the probability of being in regime i at time $t+1$ given that the market was in regime j at time t, where i and j take values in {0,1,2}. The transition probabilities satisfy $\sum_{i=0}^{2} p_{ij} = 1$.

Numerous studies, including Tyssedal and Tjostheim (1988), Hamilton (1988), Schwert (1989), Pagan and Schwert (1990), Sola and Timmermann (1994), Schaller and Van Norden (1997), Kim et al. (1998), Kim and Nelson (1998), and Mayfield (1999), have utilized the MS specification to model stock returns. The MS models offer an advantage over the linear models due to their ability to reveal patterns beyond traditional stylized facts, which only nonlinear models can generate. In general, non-linearities in stock returns may be due to: (i) speculative behavior of market participants giving rise to fads, bubbles and market crashes; and (ii) fundamental macroeconomic factors, which are inherently characterized by regime-switching related to business cycles. Several theoretical models that are consistent with regime-switching in stock returns including the rational stochastic bubble model of Blanchard and Watson (1982) and the switching fundamentals model are based on the asset pricing model of Cecchetti et al. (1990).

The three novelties of the MS herding model given in Eq. (3) which were indicated briefly earlier are discussed in more detail as follows. First, the stock returns of GCC countries are allowed to follow multiple regimes. Most studies that use stochastic regime-switching to model stock returns utilize a two state or two regime MS model. Considering the switching impact of macroeconomic fundamentals due to business cycles, a two-regime model representing recessionary and expansionary periods can be considered natural. However, in this study, we use a more general approach and allow three regimes in the MS model specified in Eq. (3) as warranted by formal tests. The three-regime specification allows us to represent market states by low volatility, high volatility, and crash market conditions where each regime is associated with different mean returns and variances. Evidence obtained in this study as well as several studies including Cakmakli et al. (2011), Guidolin and Timmermann (2006) and Maheu et al. (2009) suggests that multiple regimes be required to adequately capture the dynamics of stock returns. The evidence obtained in Cakmakli et al. (2011) shows that in addition to two regimes for the bull and bear markets, there can be additional regimes that are needed to capture crashes and recoveries (Guidolin and Timmermann, 2006), or bull market corrections and bear market rallies (Maheu et al., 2009). Second, our MS specification fully allows for regime-specific volatilities by specifying regime-dependent heteroscedasticity. Indeed, regime-dependent volatilities are crucial for accurate identification of regimes for stock markets. Therefore, our model distinguishes between different market states by allowing for different levels of market volatility. Thus, the major distinction across the bear, bull and speculative markets relates to the level of volatility and the sign of returns as there are negative returns during bear markets and positive during bull and speculative markets, which is consistent with Maheu and McCurdy (2000) and Guidolin and Timmermann (2006). Finally, we further allow all parameters of the model to vary across regimes and not only the variance.

5. Empirical results

In this section, we present the results for the two models discussed above. The first model is the standard (linear) herding model which is common in the literature, and we will herein refer to it as the static model because it has constant parameters. The second model is the Markov-switching (nonlinear) model which accommodates herding over multiple regimes.

5.1. Herding based on the static model

Table 2 reports the estimates for the static return dispersion model as described in Eq. (2). As predicted by the conditional CAPM, the estimates for the linear term (α_1) are found to be significant and positive for all countries. This is due to the cross-sectional variation in stock betas, leading to greater dispersion as each stock responds differently to the market return shocks. In the case of the estimates for the coefficient (α_2) of the nonlinear variable, the static model yields negative estimates for all countries. However, the estimates of this coefficient are significant for only Saudi Arabia, Dubai and Qatar, suggesting that stock return dispersions in these markets are significantly lower during periods of large market swings, which is consistent with herding behavior in these markets.

Interestingly, the two markets that do not show herding behavior, namely Abu Dhabi and Kuwait, have a relatively lower historical standard deviation, compared to the other three markets that have herding behavior. This may suggest a possible link between the level of volatility in a market and herding behavior, which is also consistent with the finding by Blasco et al. (2012) that herding behavior is associated with higher market volatility. It may also highlight the weakness of the static model which fails to capture the potential dynamic nature of the herding behavior, thus providing further support for a model which allows testing of herding under different market regimes in which herding behavior may or may not exist.

5.2. Herding based on the regime-switching model

In order to estimate the parameters of the MS herding model in Eq. (3), given that the number of regimes is known, the likelihood is evaluated using the filtering procedure of Hamilton (1990) followed by the smoothing algorithm of Kim (1994). The log-likelihood of the MS model is a function of the parameters in Eq. (3) and the transition probabilities p_{ij}. The estimates are obtained by maximizing the log-likelihood subject to the constraint that the probabilities lie between 0 and 1 and sum to unity. The maximization is usually carried out using the expectation maximization (EM) algorithm of Dempster et al. (1977). However, in this study we use the feasible nonlinear programming approach of Lawrence and Tits (2001), which is more effective and converges faster in most cases.

The empirical procedure for building MS models suitable for our case starts with identifying a possible set of models to consider. The models vary in terms of number of regimes (k) and the specification of variance. We consider both regime-independent variance models, MS(k), and regime-dependent variance (heteroscedastic) models, MSH(k). Once a specific MS model is estimated, the next step is to test for the presence of nonlinearities in the data. It is of interest to test whether nonlinearity adds anything to the linear constant coefficient (static) model in Eq. (2). When testing the MS model against the linear alternative, or a k regime model against a $(k-1)$ regime model, the transition probabilities are not identified under the null and, therefore, the standard distribution theory does not apply.

Table 2
Estimates for the static model.

	Saudi Arabia	Kuwait	Dubai	Abu Dhabi	Qatar
α_0	0.00989*** (0.00052)	0.01320*** (0.00060)	0.00954*** (0.00079)	0.01756*** (0.00115)	0.01207*** (0.00069)
α_1	0.73026*** (0.06564)	0.72225*** (0.07531)	0.57102*** (0.05692)	0.77258*** (0.12780)	0.33189*** (0.06049)
α_2	−7.11840*** (0.80135)	−3.82260 (2.42640)	−1.74040*** (0.66843)	−1.13960 (1.98550)	−2.10880** (0.90623)
n	993	993	993	993	993
Log L	3440.29	3011.09	2245.15	2421.68	3189.22
RSS	0.05691	0.13510	0.63185	0.44279	0.09437

Notes: The table reports the estimates for $CSAD_t = \alpha_0 + \alpha_1 |R_{m,t}| + \alpha_2 R_{m,t}^2 + \varepsilon_t$. All estimations are done using the Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. The numbers in parentheses are the HAC standard errors. A significant and negative α_2 estimate implies herding.

* Represents significance at the 10% level.

** Represents significance at the 5% level.

*** Represents significance at the 1% level.

Table 3
Model selection criteria.

	Static	MS(2)	MSH(2)	MS(3)	MSH(3)
Log L					
Saudi Arabia	3440.290	3728.819	3961.412	3973.980	4191.240
Kuwait	3011.090	3829.045	4060.384	4030.496	4218.253
Dubai	2245.150	3695.603	3766.805	3770.312	3812.315
Abu Dhabi	2421.680	3099.072	3580.235	3184.308	3715.170
Qatar	3189.220	3835.676	3944.517	3980.239	4059.744
AIC					
Saudi Arabia	−6.923	−7.492	−7.959	−7.972	−8.407
Kuwait	−6.059	−7.696	−8.158	−8.092	−8.462
Dubai	−4.516	−7.421	−7.563	−7.560	−7.642
Abu Dhabi	−4.871	−6.220	−7.187	−6.381	−7.442
Qatar	−6.417	−7.703	−7.920	−7.980	−8.138

Notes: Log L is the value of the log likelihood of the model under estimated parameter values. AIC is the Akaike information criterion. The static model is the herding regression model given in Eq. (2). MS(k) is the Markov-switching model given in Eq. (3) with regime independent variance, $\varepsilon_t \sim iid(0, \sigma^2)$, and k regimes. MSH(k) is the Markov-switching model with regime dependent or heteroscedastic variance, $\varepsilon_t \sim iid(0, \sigma^2_{St})$.

Ang and Bekaert (2002) suggest that, based on Monte Carlo evidence, the test based on the likelihood-ratio statistic between the estimated model and the derived linear model is approximately $\chi^2(q)$ distributed, where q is equal to the number of restrictions plus the nuisance parameters, i.e., free transition probabilities, that are not identified under the null. We report p-values both based on the conventional χ^2 distribution with q degrees of freedom and also the approximate upper bound for the significance level of the LR statistic as derived by Davies (1987). Once the nonlinearity is established, we choose the number of regimes and the type of MS model based on both the likelihood-ratio statistic as computed above and the Akaike information criterion (AIC). Psaradakis and Spagnolo (2003) and Krolzig (1997) suggest selecting the number of regimes and the type of the MS model using AIC and, using Monte Carlo experiment, Psaradakis and Spagnolo (2003) show that AIC is generally successful in selecting the correct model.

Table 3 reports the log likelihoods and AICs for the static model and for variants of herding models, 2- and 3-regime heteroscedastic MSH variants and homoscedastic MS variants. The log likelihoods reported in Table 3 are then used to calculate the LR tests in the first panel of Table 4. The linear static herding model is strongly rejected at 1% level by both the standard and Davies (1987) LR tests for all five GCC markets. Therefore, all four variants of the nonlinear MS herding models are strongly favored to the static model in Eq. (2), establishing strong evidence against the linear herding model in all five markets.

Having established strong evidence against the linear model, next we determine the type of the MS model and the number of regimes. For this purpose, we use both the AIC and LR tests. The AICs reported in the second panel of Table 3 take the minimum values for the 3-regime and regime-dependent variance model MSH(3).

In the second panel of Table 4, we report formal tests for testing the heterogeneous variance models and the 2-regime models against the 3-regime models. The LR tests reported in the table reject MS(2) against MS(3), and MSH(2) against MSH(3) at the 1% level by both the traditional and Davies tests, for all markets. In all cases, the regime-independent variance models MS(k) are strongly rejected in favor of the heterogeneous variance models MSH(k) for all countries. Combining the formal test results in the second panel of Table 4 and the AIC values in the second panel of Table 3, we establish strong evidence in favor of the MSH(3) models for all five markets, suggesting the presence of three market regimes for these GCC stock returns.

It is still also possible that the third regime is spurious and corresponds to few spikes in the data. Nielsen and Olesen (2001) find that the third regime for Danish stock market is a figment of the data which disappears when dummy variables are included corresponding to few spikes in the data. For this purpose, in order to check the robustness of the three-regime specification, we include in the model several combinations of dummies that correspond to spikes in the CSAD values exceeding three

Table 4
Model selection tests.

	H_0: Static H_1: MS(2)	H_0: Static H_1: MSH(2)	H_0: Static H_1: MS(3)	H_0: Static H_1: MSH(3)
Saudi Arabia	577.058*** (0.000) [0.000]	1042.244*** (0.000) [0.000]	1067.380*** (0.000) [0.000]	1501.900*** (0.000) [0.000]
Kuwait	1635.910*** (0.000) [0.000]	2098.588*** (0.000) [0.000]	2038.812*** (0.000) [0.000]	2414.326*** (0.000) [0.000]
Dubai	2900.906*** (0.000) [0.000]	3043.310*** (0.000) [0.000]	3050.324*** (0.000) [0.000]	3134.330*** (0.000) [0.000]
Abu Dhabi	1354.784*** (0.000) [0.000]	2317.110*** (0.000) [0.000]	1525.256*** (0.000) [0.000]	2586.980*** (0.000) [0.000]
Qatar	1292.912*** (0.000) [0.000]	1510.594*** (0.000) [0.000]	1582.038*** (0.000) [0.000]	1741.048*** (0.000) [0.000]
	H_0: MS(2) H_1: MSH(2)	H_0: MS(2) H_1: MS(3)	H_0: MSH(2) H_1: MSH(3)	H_0: MS(3) H_1: MSH(3)
Saudi Arabia	465.186*** (0.000) [0.000]	490.322*** (0.000) [0.000]	459.656*** (0.000) [0.000]	434.520*** (0.000) [0.000]
Kuwait	462.678*** (0.000) [0.000]	402.902*** (0.000) [0.000]	315.738*** (0.000) [0.000]	375.514*** (0.000) [0.000]
Dubai	142.404*** (0.000) [0.000]	149.418***(0.000) [0.000]	91.020*** (0.000) [0.000]	84.006*** (0.000) [0.000]
Abu Dhabi	962.326*** (0.000) [0.000]	170.472*** (0.000) [0.000]	269.870*** (0.000) [0.000]	1061.724*** (0.000) [0.000]
Qatar	217.682*** (0.000) [0.000]	289.126*** (0.000) [0.000]	230.454*** (0.000) [0.000]	159.010*** (0.000) [0.000]

Notes: The static model is the herding regression model given in Eq. (2). MS(k) is the Markov-switching model given in Eq. (3) with a regime independent variance, $\varepsilon_t \sim iid(0,\sigma^2)$, and k regimes (0, 1 and 2), while MSH(k) is the Markov-switching model with a regime dependent or heteroscedastic variance, $\varepsilon_t \sim iid(0, \sigma^2_{St})$. H_0 specifies the model under the null hypothesis that is tested against the alternative model under H_1. Test statistics are computed as the likelihood ratio (LR) test. The LR test is nonstandard since there are unidentified parameters under the null. The χ^2 p-values with degrees of freedom equal to the number of restrictions plus numbers of parameters unidentified under the null are given in parentheses and the p-values of the Davies (1987) test are given in square brackets.

* Represents significance at the 10% level.
** Represents significance at the 5% level.
*** Represents significance at the 1% level.

standard deviations of the mean, with the restriction that no more than eight dummies will be included in any case. None of the combinations of the dummies changes the three-regime results reported in Table 4. In fact, the inclusion of the dummies even enhances the test results in favor of three market regimes in some cases. Thus, the three-regime specification for these GCC markets is not spurious and corresponds to true regimes. Indeed, examining the estimates for n_2 in Table 5, we observe that the percentage of observations corresponding to the crash regime ranges between a low of 10.17% (for Kuwait) and high of 25.06% (for Saudi Arabia) of the total number of observations, further reinforcing the three-regime specification.

Table 5 presents our estimates for the three-regime herding model. The estimates for the volatility terms (σ^2) for each state clearly differentiate each regime in terms of the level of market volatility. In the case of Kuwait, for example, the estimated variance value of 0.07188 in regime 2 (crash regime) is 26 times as high as the variance estimate of 0.00275 for regime 0 (low volatility regime), clearly suggesting the presence of more than one market regime. In the case of Saudi Arabia, the crash regime is about five times as volatile as the low volatility regime. Regarding the herding tests, we find significant evidence which suggests herding behavior in all markets during the crash regime, with the exception of Qatar which herds in the high volatility regime only. It is possible that investors follow institutional investors during high market stress periods and thus display greater herding tendencies during the crash regime than in the other two regimes. However, in Qatar, the government may manage its equity market during the crash regime, negating the tendency to herd in the crash regime, but not in the high volatility regime.

Note that the static herding model reported in Table 2 without regime disentanglement incorrectly rejects herding in Kuwait and Abu Dhabi, while in fact these two markets display herding behavior during the crash regime only. These findings are consistent with earlier studies including Christie and Huang (1995) and Chang et al. (2000), suggesting that investors will be more likely to suppress their own beliefs and copy the behavior of others during periods of market stress. Therefore, the regime-switching framework appropriately captures the rationale behind the testing methodology which is based on the relationship between return dispersions and market returns during periods of market stress. The only exception is Qatar where we find evidence of herding in the high volatility regime, but not in the crash regime, which can still be characterized by market stress. As indicated earlier, one possible reason for the difference in herding behavior in Qatar is the presence of government interventions in its stock market through the Qatar investment authority (QIA), which has a mandate to support the financial markets by acting as a wealth distribution mechanism. These interventions are likely to disrupt herding in this market particularly during the crash volatility regime as this powerful sovereign wealth fundenters the market as a market maker in order to reverse the negative tendencies among investors. Although it is beyond the scope of this study to determine with clarity whether governmental interventions disrupt herding behavior in financial markets, it is interesting to note that Qatar stands out from other GCC countries during the crash volatility regime. Abu Dhabi investment authority (ADIA), for example, is not allowed to invest in the local markets.

There are several important features of the MS herding model estimates as related to the transition probability estimates p_{ij} given in Table 5 and the smoothed probabilities plotted in Figs. 1–5. The transition probability estimates for switching from the crash regime to the low volatility regime, p_{02}, is essentially zero for Saudi Arabia, Dubai, Abu Dhabi and Qatar and about 20% for Kuwait, suggesting that most of these markets do not switch directly from a crash to tranquility, and that high volatility regime follows crashes, creating volatility clustering following the crashes. In all GCC markets, with the exception of Dubai, the transition probability estimates for switching from low to high volatility, p_{10}, are very low (ranging from 1% for Saudi Arabia to 5.6% for Qatar), which implies that a crash is necessary to move from low to high volatility for these markets. With the exception of Kuwait and Dubai, this finding is reinforced by the much higher transition probability (p_{12}) estimates of switching from crash regime in one period to high volatility in the next, ranging from 3.87% (Saudi Arabia) to 75.14% (Abu Dhabi). Overall, these empirical results regarding transition probabilities suggest that the crash regime is the intermediate regime between low volatility and high volatility. It is important to note that this is different from the transition structure for developed markets which has the common order “low, high, crash volatility’ that provides investors a “warning” of a looming crash expected to follow periods of increased volatility. On the other hand, as the findings suggest, a high volatility

Table 5
Estimates for the herding models under regime switching.

Parameter	Saudi Arabia	Kuwait	Dubai	Abu Dhabi	Qatar
$\alpha_{0,0}$	0.00761*** (0.00015)	0.01960*** (0.00103)	0.00532*** (0.00043)	0.00925*** (0.00026)	0.00847*** (0.00026)
$\alpha_{0,1}$	0.01369*** (0.00035)	0.01178*** (0.00019)	0.00983*** (0.00067)	0.01474*** (0.00032)	0.01271*** (0.00037)
$\alpha_{0,2}$	0.02157*** (0.00109)	0.03072 (0.02485)	0.01897*** (0.00201)	0.06807*** (0.00396)	0.02258*** (0.00119)
$\alpha_{1,0}$	0.21648*** (0.02595)	0.67569*** (0.15610)	0.32766*** (0.05238)	0.79331*** (0.04161)	0.18956*** (0.03805)
$\alpha_{1,1}$	0.04484 (0.05637)	0.63902*** (0.04539)	0.41039*** (0.08012)	0.51811*** (0.03109)	0.28203*** (0.02904)
$\alpha_{1,2}$	0.51126*** (0.08352)	13.38590** (5.55400)	0.49762*** (0.08300)	0.05584 (0.43550)	0.16106 (0.10270)
$\alpha_{2,0}$	0.76740 (0.54940)	8.09068* (4.74000)	2.80074*** (0.57890)	3.26055 (6.00300)	0.80387 (0.87500)
$\alpha_{2,1}$	4.93293*** (1.79900)	−1.37339 (1.90900)	−1.13111 (1.67400)	1.97237*** (0.46230)	−2.49215*** (0.41150)
$\alpha_{2,2}$	−6.39345*** (1.04300)	−8.06733*** (1.72200)	−1.59927** (0.73610)	−4.22985*** (0.80230)	−0.84838 (1.51300)
σ_0^2	0.00180*** (0.00007)	0.00275*** (0.00008)	0.00192*** (0.00018)	0.00272*** (0.00011)	0.00242*** (0.00012)
σ_1^2	0.00297*** (0.00013)	0.00499*** (0.00033)	0.00417*** (0.00031)	0.00347*** (0.00014)	0.00334*** (0.00013)
σ_2^2	0.00896*** (0.00041)	0.07188*** (0.01287)	0.00881*** (0.00067)	0.02370*** (0.00178)	0.00816*** (0.00048)
p_{00}	0.98482	0.92674	0.65773	0.94935	0.93778
p_{01}	0.02075	0.00000	0.16836	0.04576	0.05149
p_{02}	0.00000	0.20862	0.00000	0.00611	0.00000
p_{10}	0.01023	0.04660	0.34227	0.03478	0.05630
p_{11}	0.95900	0.97370	0.75692	0.76475	0.91682
p_{12}	0.03873	0.00000	0.23219	0.75138	0.11424
p_{20}	0.00494	0.02666	0.00000	0.01586	0.00592
p_{21}	0.02025	0.02630	0.07472	0.18948	0.03169
p_{22}	0.96127	0.79138	0.76781	0.24251	0.88576
n_0	406	322	274	412	376
τ_0	67.67	15.33	3.91	22.89	17.90
n_1	338	570	567	465	470
τ_1	28.17	40.71	5.50	4.51	13.82
n_2	249	101	152	116	147
τ_2	27.67	5.05	4.47	1.29	9.19
n	993	993	993	993	993
Log L	4191.240	4218.253	3812.315	3715.170	4059.744
AIC	−8.407	−8.462	−7.642	−7.442	−8.138
LR	1501.90 (0.0000)***	2414.30 (0.0000)***	3134.33 (0.0000)***	2586.98 (0.0000)***	1741.05 (0.0000)***
Davies test	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***

Notes: This table presents the estimates of the three regime MSH model given in Eq. (3). The sample period covers from 7/9/2006 to 9/28/2011 with a total number of 993 observations for each country. Robust standard errors are reported in parentheses, which are obtained using the sandwich estimator of Huber (1967) and White (1982) based on the outer product of gradients and the second derivative matrix. n is the total number of observations, n_k is the number of observations in regime k, τ_k is the duration of regime k, and LR test is the linearity test. The LR test is nonstandard since there are unidentified parameters under the null. The χ^2 p-values with degrees of freedom equal to the number of restrictions plus numbers of parameters unidentified under the null are given in parentheses and the p-values of the Davies (1987) test are given in square brackets.

* Represents significance at the 10% level.

** Represents significance at the 5% level.

*** Represents significance at the 1% level.

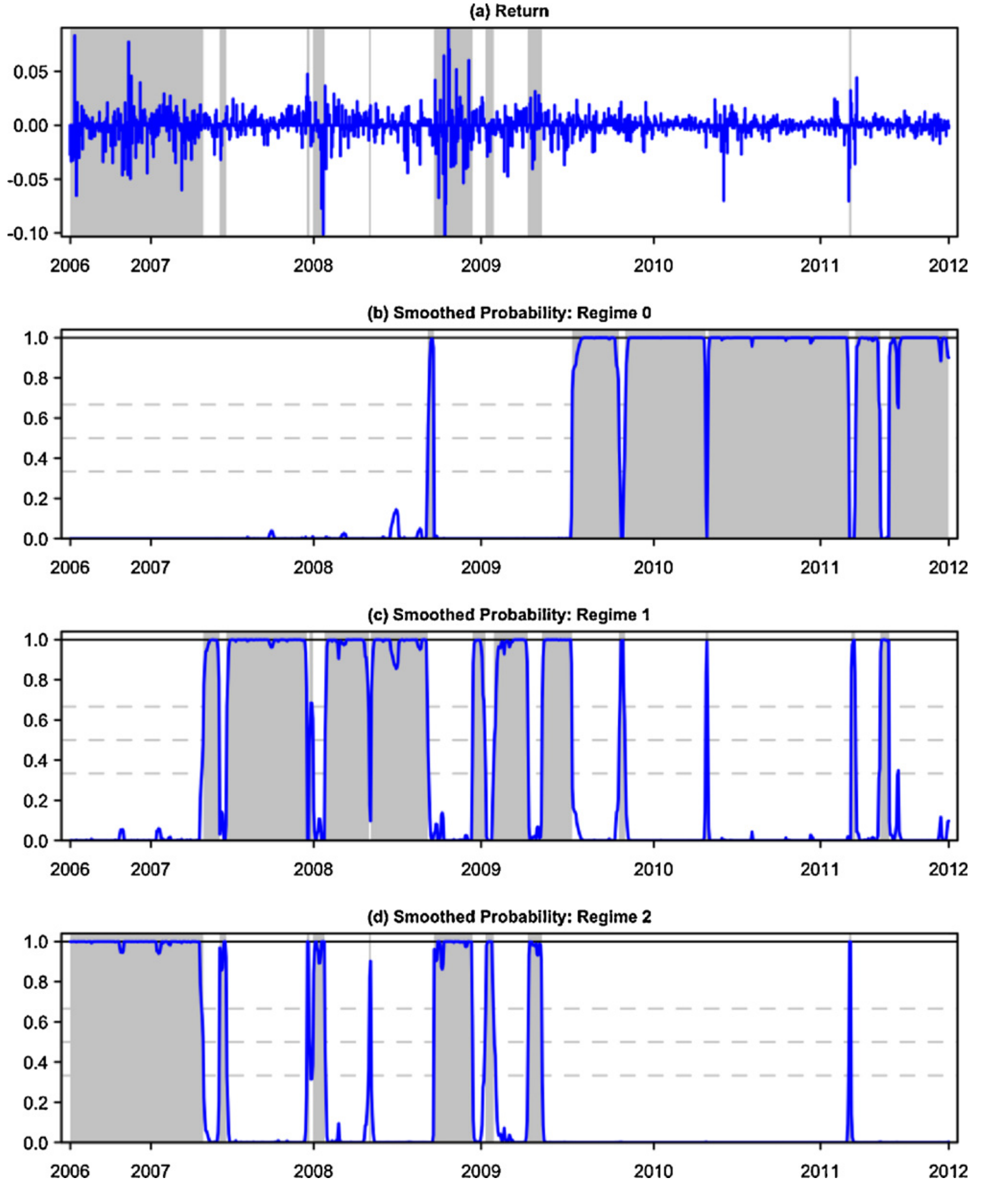

Fig. 1. Returns and transition probabilities of the 3-regime nonlinear MS model for Saudi Arabia stock market.

regime occurring right before the crash is rarely observed in GCC markets. That is, crashes are swift and the occurrence of increased volatility right before crashes is not commonly observed in the GCC markets. However, crash periods are associated with 'extreme' volatility and the periods following the crashes are characterized by high but not extreme volatility in the GCC markets, leading to volatility clustering. Therefore, crashes are hard to predict from volatility changes in the GCC markets, since volatility does not increase and the crashes occur following low volatility regimes.

Regarding the durations of the market regimes, we observe that the average duration of the crash regime ranges from a low of 1.29 days for Abu Dhabi and a high of 27.67 days for Saudi Arabia. This

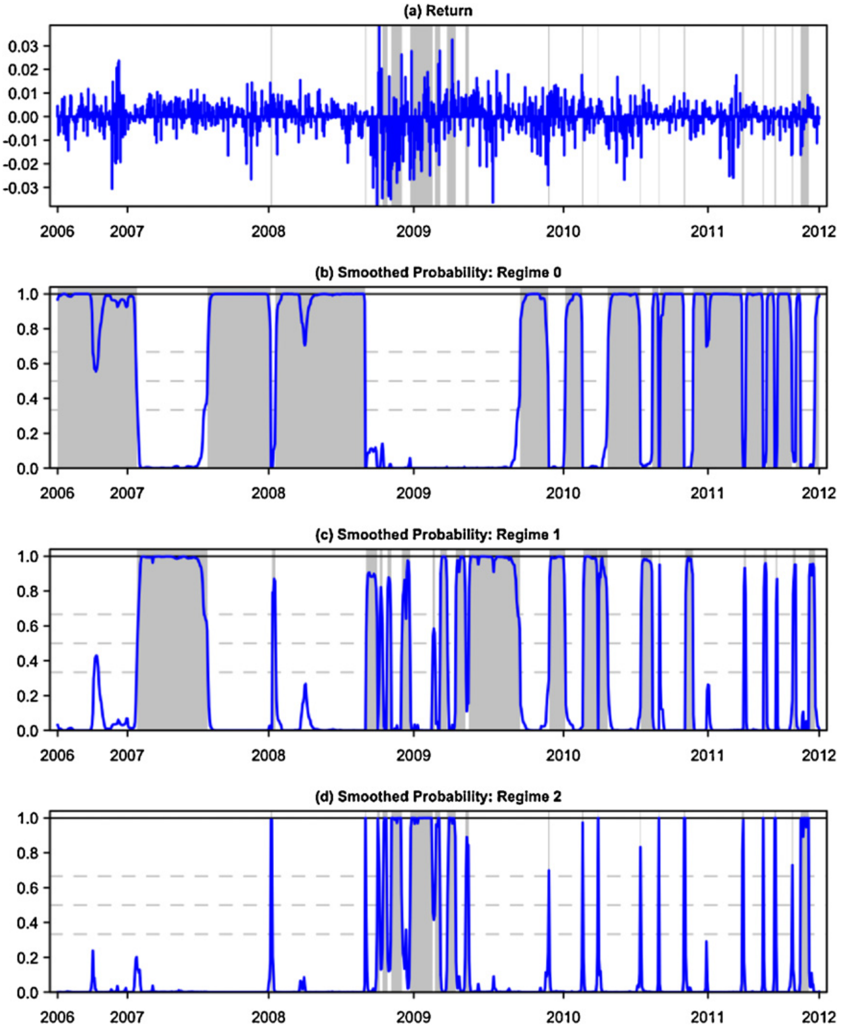

Fig. 2. Returns and transition probabilities of the 3-regime nonlinear MS model for Kuwait stock market.

implies that the crash regime is transitory and no policy intervention is required. Interestingly, the crash regime is highly persistent for Saudi Arabia with a 96% probability of staying in this regime (i.e., the crash) when the previous regime was also the crash regime. It is much less persistent for Abu Dhabi where the corresponding probability is 24%. For the low volatility regime, the average duration ranges from 3.91 days (Dubai) to 67.67 days (Saudi Arabia). In the case of the high volatility regime, the average duration varies from a low of 4.51 days for Abu Dhabi to a high of 40.71 for Kuwait.

The most noteworthy feature of the smoothed probability estimates plotted in Figs. 1–5 is the order of the regime changes. Smoothed probability estimates are another way to look at the transition probabilities. The smooth probability advantage is that it provides a perspective view of how regimes are ordered over time. In general, the order of the regime changes that is indicated by the gray areas in the figures is: the low volatility is followed by the crash, and the high volatility follows the crash (LCH). The LCH order consistently holds for all markets for most periods. For instance, we observe that Kuwait is mostly in the low volatility regime until the end of 2008. Then, a crash regime becomes active at the end of 2008 and early 2009, each of which is followed by the high volatility regime. Indeed, Kuwait

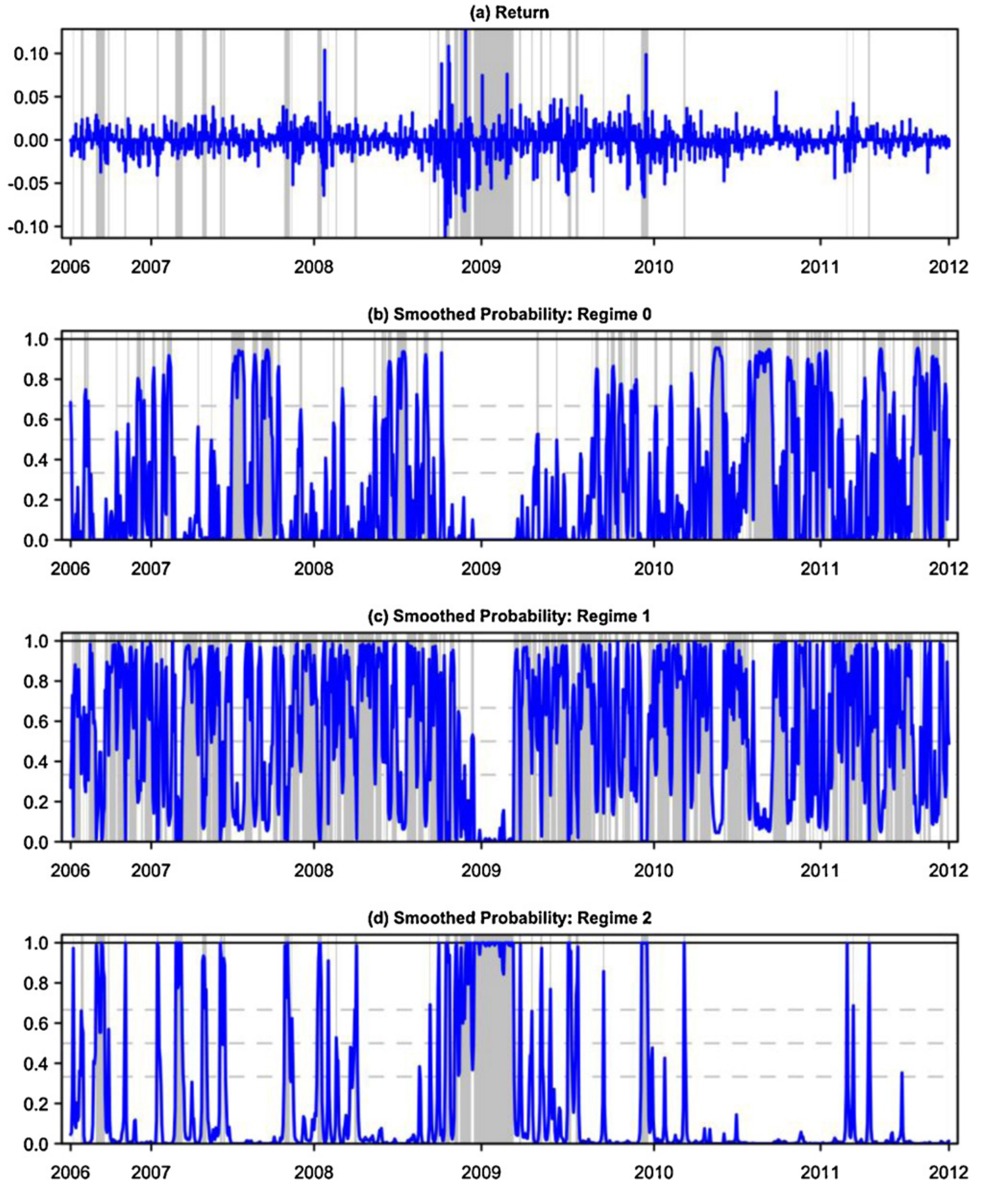

Fig. 3. Returns and transition probabilities of the 3-regime nonlinear MS model for Dubai stock market.

stock market stays in the high volatility regime until early 2010 and moves to low volatility for a few months. The extreme or crash volatility periods from the end of 2008 to early 2009 are mostly followed by periods of high volatility. Consider now the Saudi Arabian market where the most prevalent crash is from 2006 to until mid-2007. The high volatility period in this market then follows the crash until mid-2009, with the low volatility regime becoming active since then. The strong LCH order of the regimes in GCC markets is noteworthy in all periods and should be distracting for investors.

Panels (a) in Fig. 1 through Fig. 5 display returns, along with periods where herding is detected. In Fig. 1(a), for example, we see that herding is persistent in Saudi Arabia from mid-2006 to mid-2007,

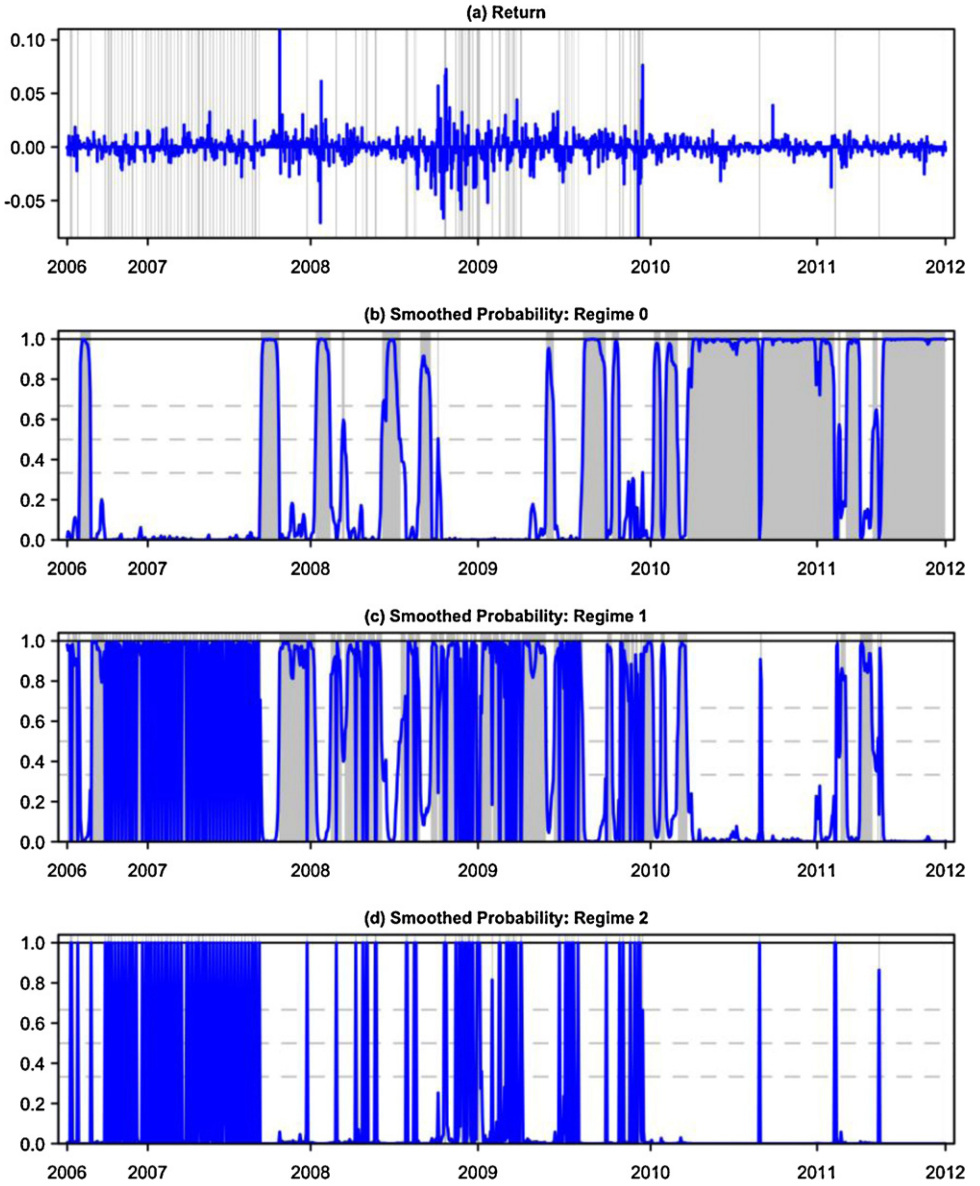

Fig. 4. Returns and transition probabilities of the 3-regime nonlinear MS model for Abu Dhabi stock market.

part of 2008 and 2009. These periods certainly witnessed extreme volatility and several crashes such as the real estate crash and the 2007/2008 global financial crisis. Herding is not observed in the crash regime after mid-2009 where the market stayed in the low volatility regime which does not have herding. Qatar is the second country where herding is detected for repeated long periods as shown in Fig. 5(a). Fig. 5(c) further suggests that this occurs during the high volatility regime, not the crash regime. The stock market in Qatar displays herding almost in all periods between mid-2006 and mid-2010 and in 2001. The support for herding is stronger and more persistent for the most volatile periods in the high volatility regime.

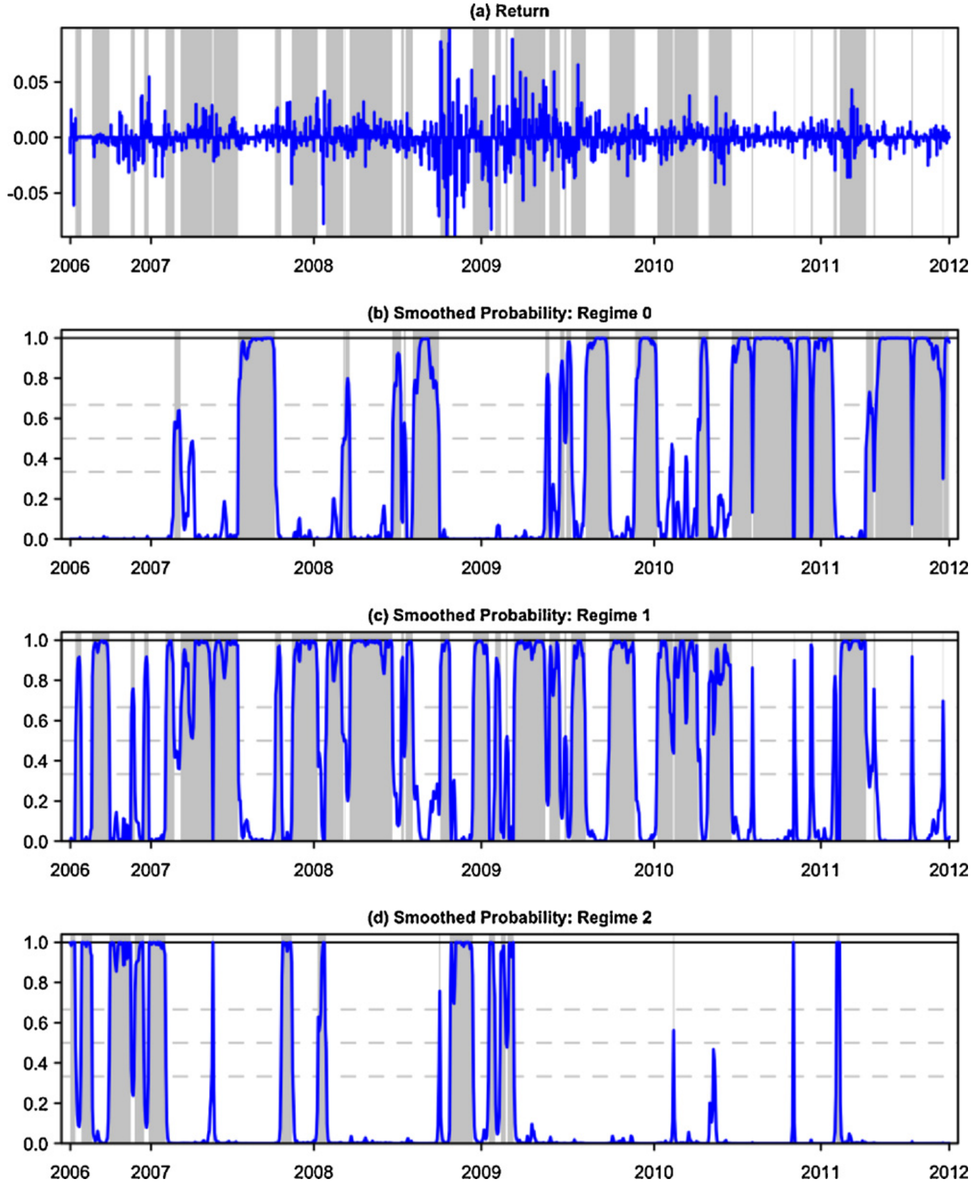

Fig. 5. Returns and transition probabilities of the 3-regime nonlinear MS model for Qatar stock market. *Note*: See Fig. 1.

In the case of Kuwait (Fig. 2(a)), herding is present for short periods, particularly during the end of 2008 and until mid-2009. We observe that periods of herding in Kuwait are shorter and less prevalent than in Saudi Arabia. On the other hand, in Dubai, herding is more widespread than in Kuwait. Both Dubai and Kuwait display persistent herding during the period between mid-2008 and mid-2009 which is not surprising as this period coincides with the height of the recent Great Recession. Finally, herding in Abu Dhabi is persistent up to the end of 2007 and is intermittent during the Great Recession period between 2008 and 2009. Abu Dhabi weathered the Great Recession era much better

Table 6
Estimates of cross-market herding model MSH(3) under regime switching.

	Panel A: Saudi Arabia *Originating market*				Panel B: Kuwait *Originating market*			
	Kuwait	Dubai	Abu Dhabi	Qatar	S. Arabia	Dubai	Abu Dhabi	Qatar
$\alpha_{0,0}$	0.0072*** (0.0003)	0.0076*** (0.0002)	0.0069*** (0.0002)	0.0070*** (0.0003)	0.0106*** (0.0002)	0.0101*** (0.0004)	0.0102*** (0.0003)	0.0100*** (0.0003)
$\alpha_{0,1}$	0.0091*** (0.0006)	0.0123*** (0.0004)	0.0117*** (0.0004)	0.0086*** (0.0005)	0.0127*** (0.0006)	0.0137*** (0.0005)	0.0143*** (0.0005)	0.0123*** (0.0007)
$\alpha_{0,2}$	0.0177*** (0.0043)	0.0212*** (0.0016)	0.0191*** (0.0013)	0.0223*** (0.0022)	0.0309*** (0.0042)	0.0315*** (0.0029)	0.0301*** (0.0029)	0.0279*** (0.0034)
$\alpha_{1,0}$	0.2215*** (0.0260)	0.2369*** (0.0275)	0.2072*** (0.0261)	0.2454*** (0.0267)	0.6973*** (0.0894)	0.5903*** (0.0639)	0.5725*** (0.0716)	0.6718*** (0.0740)
$\alpha_{1,1}$	0.2234*** (0.0408)	0.0258 (0.0531)	0.1853*** (0.0391)	0.2664*** (0.0375)	0.5488*** (0.0501)	0.5445*** (0.0720)	0.5276*** (0.0562)	0.5349*** (0.0603)
$\alpha_{1,2}$	0.6081*** (0.1021)	0.5391*** (0.0871)	0.5899*** (0.0832)	0.6854*** (0.1085)	−0.2128 (0.5592)	0.0990 (0.3472)	0.0274 (0.3536)	−0.5469 (0.5966)
$\alpha_{2,0}$	0.7319 (0.5613)	0.5408 (0.5477)	1.4941** (0.7361)	0.3986 (0.5349)	1.6340 (2.3240)	2.5273 (5.1680)	5.0624 (2.6820)	2.8035 (3.2650)
$\alpha_{2,1}$	−0.7224 (0.8355)	5.0261*** (1.5860)	0.3178 (0.8562)	−1.7779** (0.7406)	13.0162 (20.5100)	2.0959 (10.3300)	4.8017 (11.1200)	20.4736 (20.6100)
$\alpha_{2,2}$	−7.6342*** (1.2210)	−6.9506*** (1.1270)	−7.4561*** (1.1270)	−8.8865*** (1.3390)	−7.1273** (2.8360)	−3.0823** (1.3170)	−2.3435** (1.1678)	−7.1088*** (2.4900)
$\alpha_{3,0}$	0.0215 (0.0146)	0.0028 (0.0159)	0.0167** (0.0077)	0.0282 (0.0191)	0.1913*** (0.0373)	0.0452*** (0.0156)	0.0045 (0.0081)	0.1484*** (0.0452)
$\alpha_{3,1}$	0.2740*** (0.0330)	0.1179*** (0.0238)	0.0265*** (0.0099)	0.2866*** (0.0302)	0.0613*** (0.0107)	0.0511*** (0.0146)	0.0297*** (0.0057)	0.0661*** (0.0160)
$\alpha_{3,2}$	0.3525 (0.2799)	0.0089 (0.0734)	0.0468** (0.0229)	0.0176 (0.0979)	0.0054 (0.2061)	−0.0900 (0.0955)	−0.0277 (0.0447)	0.3492** (0.1754)
$\alpha_{4,0}$	−0.0682 (0.9619)	−0.1588 (0.1773)	0.0674 (0.1772)	0.3935 (0.3190)	0.1678 (0.2925)	0.2875*** (0.1570)	0.1355 (0.3440)	0.4696** (0.2063)
$\alpha_{4,1}$	−1.7596 (1.3580)	−0.9715*** (0.3256)	0.0183 (0.2484)	0.6360*** (0.1950)	−0.0818 (0.1351)	−0.1357*** (0.05711)	−0.4625*** (0.1576)	0.1583 (0.2705)
$\alpha_{4,2}$	−7.0065 (6.0100)	0.3606*** (0.3920)	0.5174 (0.8800)	1.0424 (0.6464)	−0.6146*** (0.2190)	−0.1120*** (0.04840)	−0.7086*** (0.1985)	−1.0528*** (0.2748)
σ_0^2	0.0018*** (0.0001)	0.0019*** (0.0001)	0.0014*** (0.0001)	0.0018*** (0.0001)	0.0024*** (0.0001)	0.0020*** (0.0001)	0.0020*** (0.0001)	0.0021*** (0.0001)
σ_1^2	0.0035*** (0.0001)	0.0029*** (0.0001)	0.0030*** (0.0001)	0.0035*** (0.0001)	0.0031*** (0.0002)	0.0026*** (0.0001)	0.0027*** (0.0001)	0.0028*** (0.0001)
σ_2^2	0.0093*** (0.0005)	0.0090*** (0.0004)	0.0087*** (0.0004)	0.0093*** (0.0005)	0.0100*** (0.0011)	0.0085*** (0.0007)	0.0083*** (0.0006)	0.0085*** (0.0008)
n	993	993	993	993	993	993	993	993
Log L	4209.327	4196.5925	4198.6862	4214.0415	4286.7418	4304.2425	4309.5515	4312.4324
AIC	−8.4297	−8.4040	−8.4062	−8.4392	−8.5876	−8.6168	−8.6275	−8.6332
LR	1526.70	1482.90	1447.10	1427.30	972.38	976.42	1008.80	975.73
p-Value of LR	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Davies test	[0.000]***	[0.000]***	[0.0000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Table 6 (*continued*)

	Panel C: Dubai *Originating market*				Panel D: Abu Dhabi *Originating market*			
	S. Arabia	Kuwait	Abu Dhabi	Qatar	S. Arabia	Kuwait	Dubai	Qatar
$\alpha_{0,0}$	0.0057*** (0.0005)	0.0057*** (0.0005)	0.0047*** (0.0004)	0.0051*** (0.0006)	0.0086*** (0.0004)	0.0091*** (0.0005)	0.0100*** (0.0000)	0.0086*** (0.0004)
$\alpha_{0,1}$	0.0077*** (0.0010)	0.0085*** (0.0010)	0.0084*** (0.0006)	0.0094*** (0.0009)	0.0127*** (0.0005)	0.0108*** (0.0006)	0.0095*** (0.0003)	0.0122*** (0.0005)
$\alpha_{0,2}$	0.0265*** (0.0041)	0.0104*** (0.0025)	0.0170*** (0.0020)	0.0179*** (0.0024)	0.0576*** (0.0061)	0.0536*** (0.0091)	0.0629*** (0.0055)	0.0585*** (0.0065)
$\alpha_{1,0}$	0.3989*** (0.0324)	0.3330*** (0.0404)	0.3720*** (0.0305)	0.3529*** (0.0528)	0.7533*** (0.0430)	0.5178*** (0.0475)	0.6697*** (0.0017)	0.7819*** (0.0436)
$\alpha_{1,1}$	0.5228*** (0.0522)	0.3978*** (0.0450)	0.4738*** (0.0422)	0.4124*** (0.0363)	0.6524*** (0.0496)	0.5971*** (0.0355)	0.6242*** (0.0353)	0.5662*** (0.0427)
$\alpha_{1,2}$	0.4534*** (0.1172)	0.4911*** (0.0857)	0.3381*** (0.1131)	0.4905** (0.2055)	0.0297 (0.3776)	0.1301 (0.3905)	0.0836 (0.4521)	0.1373 (0.3967)
$\alpha_{2,0}$	−1.1846* (0.5701)	2.8875*** (0.6319)	−0.0271 (0.2470)	−0.8055 (0.6407)	3.1146*** (4.1150)	1.6425 (4.2880)	2.1065*** (4.5220)	1.3490 (4.3430)
$\alpha_{2,1}$	−1.3042* (0.7061)	−1.1566 (0.7521)	0.8658 (1.6540)	−0.7217 (0.4635)	−2.582382	−2.5736*** (0.6641)	−1.4426 (0.9631)	0.2550 (1.0450)
$\alpha_{2,2}$	−1.5999*** (1.1770)	−1.5943* (0.8687)	−2.1062*** (0.6576)	−0.8290 (0.2880)	−3.0140*** (0.9168)	−9.9760*** (0.6961)	−3.9154*** (0.0202)	−3.5937*** (1.0440)
$\alpha_{3,0}$	0.0524(0.0219)	−0.0319 (0.0198)	0.0340*** (0.0088)	0.0175 (0.0488)	0.0785*** (0.0292)	0.0473** (0.0232)	0.1052*** (0.0010)	0.0634** (0.0291)
$\alpha_{3,1}$	0.2483*** (0.0454)	0.0646 (0.0598)	0.0365** (0.0153)	0.0108 (0.0516)	0.0725*** (0.0215)	0.1880*** (0.0341)	0.1900*** (0.0195)	0.1331*** (0.0316)
$\alpha_{3,2}$	−0.2027 (0.1703)	0.4075*** (0.1165)	0.0899** (0.0398)	−0.0107 (0.0930)	0.4853** (0.2287)	0.8609 (0.5434)	0.2460 (0.2674)	0.4241 (0.2783)
$\alpha_{4,0}$	0.5092* (0.2660)	3.0427 (2.5580)	4.6065*** (0.5505)	0.8915** (0.4318)	0.0705 (1.8960)	−1.1911 (1.9580)	−0.7291 (1.4780)	−0.7664 (0.6823)
$\alpha_{4,1}$	0.0270 (0.5826)	−0.7916 (1.6110)	−0.5150*** (0.1995)	1.4539*** (0.3935)	0.3436 (0.2359)	3.0980*** (1.0980)	−0.0484 (0.2265)	0.0380 (0.2287)
$\alpha_{4,2}$	0.7386 (1.8030)	−4.7896*** (2.1520)	−2.8971* (1.4880)	−3.2643*** (0.9926)	−0.5244* (0.2867)	−26.4643* (16.4100)	−0.1269*** (0.0054)	−1.7414*** (0.7270)
σ_0^2	0.0028*** (0.0002)	0.0018*** (0.0002)	0.0019*** (0.0002)	0.0021*** (0.0002)	0.0027*** (0.0001)	0.0027*** (0.0001)	0.0000*** (0.0000)	0.0027*** (0.0001)
σ_1^2	0.0049*** (0.0003)	0.0039*** (0.0002)	0.0038*** (0.0002)	0.0039*** (0.0004)	0.0035*** (0.0001)	0.0034*** (0.0001)	0.0035*** (0.0001)	0.0034*** (0.0001)
σ_2^2	0.0096*** (0.0007)	0.0084*** (0.0005)	0.0090*** (0.0005)	0.0080*** (0.0006)	0.0232*** (0.0018)	0.0228*** (0.0018)	0.0234*** (0.0019)	0.0242*** (0.0018)
n	993	993	993	993	993	993	993	993
Log L	3829.228	3821.2711	3833.1541	3817.5245	3738.7069	3730.7211	3648.9640	3724.4815
AIC	−7.6641	−7.6461	−7.6660	−7.6345	−7.4798	−7.4617	−7.2970	−7.4491
LR	547.00	516.31	538.72	503.35	2315.30	2359.50	2168.60	2299.70
p-Value of LR	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Davies Test	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Table 6 (*continued*)

	Panel E: Qatar *Originating market*			
	Saudi Arabia	Kuwait	Dubai	Abu Dhabi
$\alpha_{0,0}$	0.0125*** (0.0006)	0.0121*** (0.0008)	0.0081*** (0.0003)	0.0081*** (0.0003)
$\alpha_{0,1}$	0.0059*** (0.0004)	0.0079*** (0.0004)	0.0119*** (0.0005)	0.0121*** (0.0004)
$\alpha_{0,2}$	0.0233*** (0.0022)	0.0202*** (0.0020)	0.0240*** (0.0017)	0.0203*** (0.0014)
$\alpha_{1,0}$	0.2881*** (0.0328)	0.2694*** (0.0306)	0.1848*** (0.0386)	0.2053*** (0.0390)
$\alpha_{1,1}$	0.2078*** (0.0365)	0.1926*** (0.0372)	0.2714*** (0.0302)	0.2808*** (0.0302)
$\alpha_{1,2}$	0.1485 (0.1032)	0.1311*** (0.1026)	0.1374 (0.0966)	0.1618* (0.0973)
$\alpha_{2,0}$	−2.6197*** (0.4551)	−2.4820*** (0.4107)	0.7662 (0.8471)	0.6775 (0.8609)
$\alpha_{2,1}$	0.6334 (0.8699)	0.4622 (0.9205)	−2.6501*** (0.4706)	−2.4224*** (0.5056)
$\alpha_{2,2}$	−0.8684 (1.4550)	−0.2995 (1.4750)	−0.4545 (1.4110)	−0.9738 (1.4490)
$\alpha_{3,0}$	0.0094 (0.0274)	0.0384 (0.0460)	0.0351* (0.0210)	0.0279** (0.0124)
$\alpha_{3,1}$	0.2533*** (0.0289)	0.0375 (0.0229)	0.0624** (0.0263)	0.0118 (0.0090)
$\alpha_{3,2}$	−0.0551 (0.0867)	0.1722* (0.0995)	−0.1052 (0.0736)	0.0483* (0.0259)
$\alpha_{4,0}$	0.2064 (0.2356)	1.9542 (1.3980)	−0.2075 (0.2363)	0.3813 (0.6014)
$\alpha_{4,1}$	1.0553 (0.2898)	0.8905 (1.4510)	−0.3261 (0.1227)	−0.3044*** (0.13179)
$\alpha_{4,2}$	1.7153* (0.9174)	−6.6818* (3.9620)	−0.8537** (0.4110)	−0.1452*** (0.0507)
σ_0^2	0.0035*** (0.0001)	0.0034*** (0.0001)	0.0024*** (0.0001)	0.0026*** (0.0001)
σ_1^2	0.0025*** (0.0001)	0.0024*** (0.0001)	0.0033*** (0.0001)	0.0033*** (0.0001)
σ_2^2	0.0083*** (0.0005)	0.0081*** (0.0005)	0.0080*** (0.0005)	0.0080*** (0.0004)
n	993	993	993	993
Log L	4054.4498	4068.0531	4063.4319	4054.9413
AIC	−8.1157	−8.1411	−8.1298	−8.1147
LR	640.38	791.26	787.19	736.91
p-Value of LR	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Davies test	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***

Notes: This table presents the estimates of the three regime cross-market herding MSH model given in Eq. (4): $CSAD_{k,t} = \alpha_{0,S} + \alpha_{1,S}|R_{k,t}| + \alpha_{2,S}R_{k,t}^2 + \alpha_{3,S}CSAD_{j,t} + \alpha_{4,S}R_{j,t}^2 + \varepsilon_t$. Estimation sample covers the common period 7/10/2006–9/27/2011 for which data is available for all markets on common dates. The estimates in the table are for CSAD of market k and originating market j. Robust standard errors are reported in parentheses, which are obtained using the sandwich estimator of Huber (1967) and White (1982) based on the outer product of gradients and second derivative matrix. n is the total number of observations, LR is the likelihood ratio test of linearity. The LR test is nonstandard since there are unidentified parameters under the null. The χ^2 p-values with degrees of freedom equal to number of parameters unidentified are given as p-value of LR. Davies test gives the p-values of Davies (1987) test.

* Represents significance at the 10% level.

** Represents significance at the 5% level.

*** Represents significance at the 1% level.

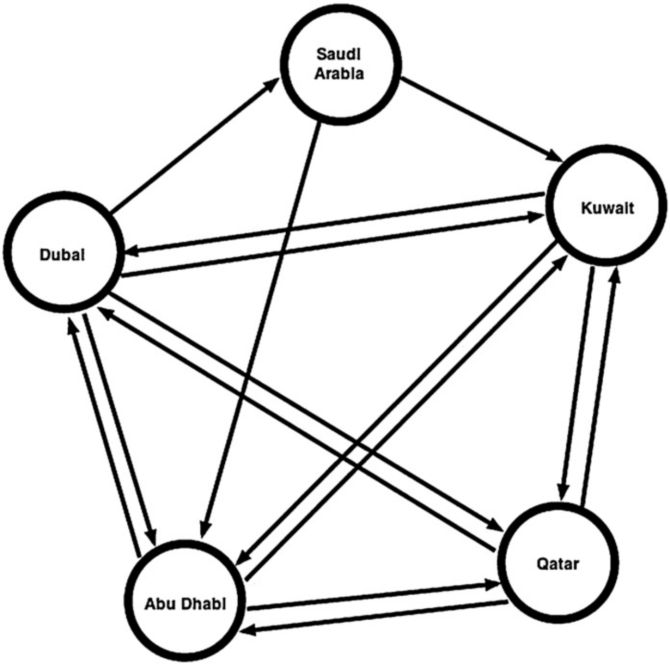

Fig. 6. Cross-herding links based on cross-market herding model under regime switching. *Note*: The figure links markets k and j based on the three regime cross-market herding MSH model given in Eq. (4): $CSAD_{k,t} = \alpha_{0,S} + \alpha_{1,S}|R_{k,t}| + \alpha_{2,S}R^2_{k,t} + \alpha_{3,S}CSAD_{j,t} + \alpha_{4,S}R^2_{j,t} + \varepsilon_t$. An arrow is drawn from market j to market k, if there is cross-herding represented by a significant coefficient $\alpha_{4,S}$ on $R^2_{j,t}$ in high-volatility regime (Regime 1) and crash regime (Regime 2), at the 1%, 5%, or 10% significance level. Direction of the arrows indicates flow of direction of cross-market herding effects.

than Kuwait and Dubai because of its huge foreign reserves and its highly conservative fiscal and investment policies.

5.3. Cross-market herding effects

The analysis so far has focused on herding behavior within each GCC market. It will be of particular interest if we detect herding comovements or spillovers among those countries. As mentioned earlier, an interesting characteristic of these countries is that they are connected through a political and economic union and share several similar socio-economic characteristics. Therefore, shocks in local markets coupled with unique geopolitical and economic uncertainties surrounding these markets (e.g., political instability, dependence on oil, etc.), can also create additional joint uncertainty on top of the global risk factors affecting these markets. This means that a market shock in one member country has the potential to be quickly transmitted to other members, institutionalizing herding mentality. For this purpose, we look into cross-market effects and examine possible herding spillover effects in these markets. More specifically, we estimate for each country k

$$CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t}R^2_{k,t} + \alpha_{3,S_t}CSAD_{j,t} + \alpha_{4,S_t}R^2_{j,t} + \varepsilon_t \tag{4}$$

where $k \neq j$, $\varepsilon_t \sim iid(0, \sigma^2_{St})$ and S_t is the random state variable defined in Eq. (3), taking values in {0,1,2}. In this model, $CSAD_{k,t}$ and $R_{k,t}$ are the cross-sectional average dispersion and the market return for country k on day t, respectively. Similarly, we incorporate in the model the squared market returns, $R^2_{j,t}$, for the remaining GCC countries to discern the possible presence of cross or inter-GCC herding. A similar model was utilized in a recent study by Chiang and Zheng (2010), but without regime switching, in order to examine the effect of the U.S. market on herding in a number of developed and emerging

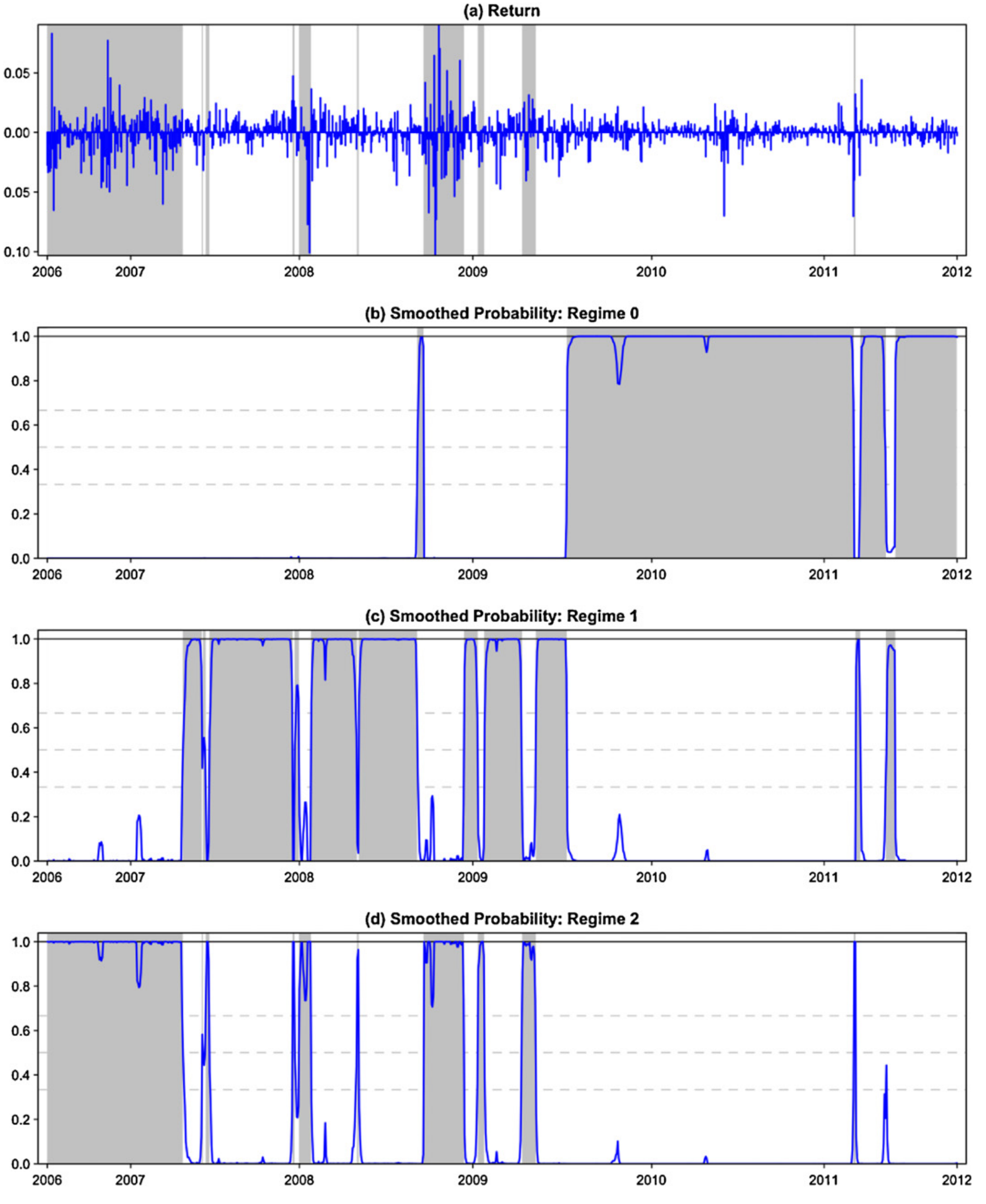

Fig. 7. Returns and transition probabilities of the 3-regime cross-market herding model under regime switching for Saudi Arabia. *Note*: Figures plot the return and estimates of the smoothed regime transition probabilities from the three regime cross-market herding MSH model given in Eq. (4) for herding transmission from Dubai to Saudi Arabia. The estimation sample covers the common period 7/9/2006–9/28/2011 for which data is available for all markets on common dates. Figure (a) plots the market return. The shaded regions in Figure (a) correspond to regimes where cross-herding is supported with statistically significant negative coefficients on squared returns of Dubai in Eq. (4). Figures (b)–(d) plot the smoothed regime probabilities for the 3-regime nonlinear MS model in Eq. (4). The shaded regions in (b)–(d) correspond to the maximum smoothed probability among the three smoothed probabilities. Regimes 0, 1, and 2 are the low, high, and the crash or extreme volatility regimes, respectively.

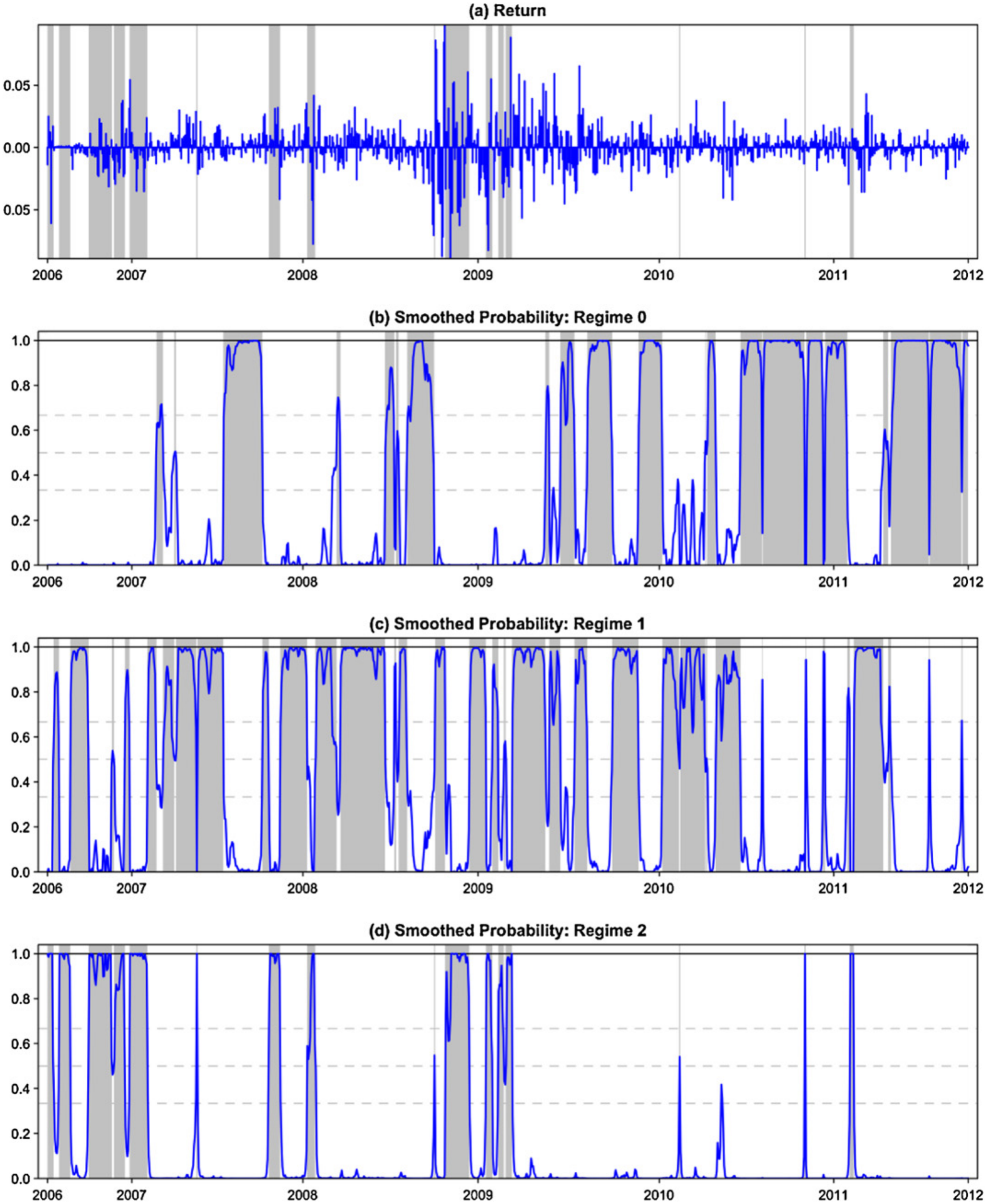

Fig. 8. Return and smoothed probability of 3-regime cross-market herding model under regime switching for Qatar. *Note*: Figures plot the return and estimates of the smoothed regime transition probabilities from three regime cross-market herding MSH model given in Eq. (4) for herding transmission from Kuwait to Qatar. Estimation sample covers the common period 7/9/2006–9/28/2011 for which data is available for all markets on common dates. Figure (a) plots the market return. The shaded regions in (a) correspond to regimes where cross-herding is supported with statistically significant negative coefficients on squared returns of Kuwait in Eq. (4). Figures (b)–(d) plot the smoothed regime probabilities for the 3-regime nonlinear MS model in Eq. (4). The shaded regions in (b)–(d) correspond to the maximum smoothed probability among the three smoothed probabilities. Regimes 0, 1, and 2 are the low, high, and the crash or extreme volatility regimes, respectively.

markets. In this model, observing a negative and significant $\alpha_{4,j}$ estimate suggests that country k tend to herd in regime j with the other country corresponding to the coefficient in the model.

Table 6 presents our estimates for the cross-market herding model in Eq. (4) for each GCC market.[5] In this table, there are three estimates for each coefficient of the models, one for each regime. What is of special interest in the tables are therefore the three estimates of $\alpha_{4,j}$, $j=0,1,2$, for the cross herding effects between GCC markets. As can be seen, those estimates are overwhelmingly significant for the crash regime for all markets except Saudi Arabia. As the world's major oil exporter, Saudi Arabia is the dominant country in the GCC as well as the Middle East and North Africa region in terms of market capitalization and GDP size. It is interesting to note that only Dubai has a unidirectional cross-herding relationship with Saudi Arabia. Note that a good portion of the investors in Dubai are from Saudi Arabia. These findings of the cross GCC herding model support herding comovements and not spillovers, and are also robust to the cross-GGC volatility shocks as represented by significant coefficients for the cross-herding return dispersion terms. Our analysis for possible herding spillover or contagion did not produce significant results.

Fig. 6 illustrates the cross-herding effects among the five GGC markets. Based on the findings presented in Table 6, an arrow is drawn from the originating market, indicating cross-herding effect of the originating market. Fig. 6 suggests that Dubai–Kuwait, Dubai–Abu Dhabi, Dubai–Qatar, Abu Dhabi–Kuwait, Abu Dhabi–Qatar, and Kuwait–Qatar display bidirectional cross-herding effects. On the other hand, we observe single direction cross-herding effects from Dubai to Saudi Arabia and from Saudi Arabia to Kuwait and Abu Dhabi. Interestingly, Saudi Arabia stands isolated from other markets as an originating market without being affected by the other GCC markets. This finding on Saudi Arabia is consistent with Hammoudeh and Aleisa (2004).

In order to illustrate the periods of cross-herding, we plot the smoothed probabilities for the cross-herding specification from Dubai to Saudi Arabia and the stock market return in Saudi Arabia in Fig. 7. In panel (a) of this figure, the gray area corresponds to periods where cross-herding is detected. First, we note that regime classifications in Fig. 7 are sharp and quite persistent. Second, cross-herding is only detected where herding occurs in both markets. The noteworthy periods of cross-herding are from 2006 to mid-2007, early 2008 and from late 2008 to mid-2009, which are consistent with herding periods in both markets. Analogously, in Fig. 8 we plot the smoothed probabilities for the cross-herding specification from Kuwait to Qatar and the stock market return in Qatar. As in the case of Saudi Arabia, regime classifications are sharp and persistent. Moreover, the cross-herding periods are from 2006 to mid-2007, early 2008 and from late 2008 to mid-2009, which are consistent with the periods when herding is observed in both markets. These are also the cross-herding periods from Kuwait to Saudi Arabia. Interestingly, these periods correspond to extreme volatilities of the greatest crash in the history of these markets. This finding strongly suggests that cross herding be also a phenomenon observed during extreme volatility or crash periods. The cross-herding regimes in other cases bear the same features analogous to what we find in Figs. 7 and 8, indicating that our cross-herding findings are consistent and real market phenomena, not statistical artifacts.

6. Conclusions and discussion of implications

The main contribution of this paper is to propose a modification to the standard herding approach employed in prior studies and utilize a new herding model that takes into account herding under different market regimes for the frontier economies of oil rich countries which have unique investment culture and economic structure. Specifically, we focus on six frontier markets in the Gulf Cooperation Council (GCC) countries – UAE (Abu Dhabi and Dubai), Kuwait, Qatar and Saudi Arabia – and estimate a three-state Markov-switching (MS) model for the cross sectional dispersions of stock returns. Unlike the standard testing methodology available in the literature, this alternative specification allows us to differentiate between different market states when herding behavior may or may not exist.

[5] Estimation of multivariate cross-herding models gives rise to co-linearity which is damaging in the case of MS models, leading to imprecise estimates and convergence problems.

Our analysis suggests the presence of three market regimes (low, high and extreme or crash volatility regimes) in the GCC stock markets. The results also demonstrate that the regime transition order goes from low to crash to high volatility, suggesting that the crash regime is the intermediate regime between the low and high volatility regimes. This behavior may be disturbing for investors in these markets because the markets can potentially crash before gearing into high volatility, without any prior signaling. This disturbing behavior in the GCC stock markets is in contrast to the common behavior of the developed markets which transition from low to high to crash.

The regime-based tests yield significant evidence of herding under the crash regime for all of the markets except Qatar which herds under the high volatility regime. Interestingly, the static herding model incorrectly rejects herding in Kuwait and Abu Dhabi, while in fact these two markets display herding behavior during the crash regime only. Our analysis of the cross-market herding effects supports herding comovements and not spillovers which suggest that the GCC markets face common factors that affect them simultaneously, particularly in times of extreme volatility. This makes investment and portfolio diversification in those markets potentially dangerous during periods of speculation and high risk where crashes come after tranquility, without any prior signaling. A crash in those markets can be likened to a chain automobile accident. This means that investors who seek portfolio diversification benefits will not be able to find them in these markets during periods of market stress. For this purpose, domestic investors in these markets should diversify their GCC portfolios with safety stocks (e.g., high dividend stocks) from outside the GCC region. Alternatively, foreign hedging instruments can be utilized to manage market risks in the GCC. However, it must be noted that increased multi-market volatility can provide profitable investment opportunities through options contracts, and this creates a potential for market makers to introduce risk products to GCC investors. Risk products tied to multi-market volatility in the GCC markets may have a structure similar to hurricane derivatives or credit default swaps offered in the United States.

Regarding policy implications, regulators should develop safety nets and circuit breakers that can stop crashes in their tracks and propose rules to prevent instability in order to avoid an avalanche of market crashes. This could be done by establishing a pan GCC agency with the goal of developing, coordinating and implementing strategic plans to manage financial crisis at the union. Furthermore, margin transactions in these markets should be regulated and effectively monitored as practices such as naked short selling are deadly for these markets. Regulators should also provide incentives to institutionalize hedging instruments in order to enhance hedging effectiveness to deal with market crashes.

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