# Does speculation in the oil market drive investor herding in net exporting nations?

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## Abstract

This paper examines whether speculation in the global oil market contributes to herd behavior in the stock markets of net exporting nations. Using firm level data from the Gulf Arab stock markets, we show that investors display herd behavior during periods of high volatility while anti-herding is prevalent during calm markets. Anti-herding in the stock market is also found to be positively related to speculative activities in the global oil market as investors use signals from the oil market in their trades by trading away from the market consensus. We argue that traders take the speculative signals from the oil market as a sign of positive expectations and try to generate superior profits by going against the crowd in their local market.



**JEL Classification Code:** C32, G14, G15

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## 1. Introduction

Herd behavior in financial markets has been examined in numerous studies over the past several decades while the literature has witnessed a surge in herding studies particularly following the 2007/08 global financial crisis that shook financial markets to the core. As the well-established theories of financial returns are based on the fundamental assumption of investor rationality, herd behavior is often associated with irrational or anomalous investor behavior that may destabilize market prices and create excess volatility (e.g. Bikhchandani and Sharma, 2001; Blasco et al., 2012). Despite the multitude of studies that provide theoretical explanations as to why investors would act in herds, the empirical literature, however, has largely focused on testing the presence of herd behavior in different contexts without putting much attention to the factors that potentially drive such behavior among investors. Much of the reason for this is that the traditional herding tests have utilized either low frequency data or static models in their analyses that limited the insight to the dynamic nature of how herding in the market evolves over time.

The role of underlying factors that potentially affect investor behavior is particularly important in the case of emerging markets as investors' trades can be highly sensitive to external (global) market shocks due to limited diversification opportunities available domestically. The main goal of this study is to examine, using a dynamic, time-varying parameter model, whether volatility and speculation in the oil market contributes to herding among local stock investors in major exporting nations. By doing so, this study contributes to both the literature on investor herding and the oil-stock market nexus from both a behavioral and econometric perspective.

The empirical analysis focuses on the stock markets of the oil-rich Gulf Cooperation

Council (GCC) countries as these markets provide fertile ground for a study of how external factors, in this case oil market dynamics, relate to investor behavior in stock markets. The region possesses about 48% of the world's proved oil reserves and controls one third of the world oil production, with Saudi Arabia ranking first in the global oil exporter ranking, while UAE and Kuwait are ranked third and sixth, respectively.[1] These economies are heavily dependent on income from energy exports with energy export revenues as a percentage of total exports as high as 90% in the case of Saudi Arabia. On the other hand, the stock markets of these countries are classified as emerging (or frontier) markets due to a number of market characteristics including market size, depth and/or investment restrictions into these markets, among others.[2] It can thus be argued that the heavy dependence of these economies on energy exports coupled with sector concentration due to limited supply of stocks and the lack of alternative domestic financial assets, expose stock portfolios to significant oil price risks that, unlike in the case of advanced markets, can be difficult to diversify away (Mansur and Delgado, 2008; Balcilar et al, 2013; Demirer et al., 2015). This unhedged risk exposure, in turn, can make investors' trading behavior particularly sensitive to oil market dynamics and contribute to herd behavior as investors overreact to common information signals or recent news (Shleifer and Summers, 1990).

Furthermore, unlike the stock markets in other emerging nations such as Poland or Chile, Gulf exchanges are largely dominated by retail traders who are less informed, trade for non-informational reasons (Hirose et al., 2009) and possibly exhibit greater herding tendencies. These unique features, thus, make GCC stock markets particularly interesting for a study of how herd behavior may be driven by external factors, in this case the oil market, and allow for

[1] BP Statistical Review of World Energy (June 2015) and the CIA World Factbook (2014).
[2] According to MSCI, only Qatar and UAE are classified as emerging, while Kuwait and Saudi Arabia are classified as frontier and standalone markets, respectively. (https://www.msci.com/market-classification)

a novel take on the oil-stock market nexus from a behavioral perspective.

From an econometric perspective, the dynamic, Markov switching time varying parameter (MS-TVP) herding model proposed in this study offers several improvements in that it not only accommodates different market regimes when herding may or may not be present, but it also estimates the time-variation in herding parameters, allowing us to directly relate the level of herding in the market to the time variation in oil market dynamics. Finally, we perform comparative analyses using a rich cross-section of firm characteristics that include industry and size classification as well as compliance to religious investment rules to see if firm characteristics play any role on investors' tendencies to display herd behavior. By doing so, this study contributes to our understanding of the dynamics of herd behavior and the transmission of oil price shocks to equity markets in a number of different ways.

Looking ahead, our findings show that the level of herding indeed exhibits a dynamic pattern in which the market switches between herding and anti-herding, more frequently in the case of investors trading large cap and Islamic stocks. While investor herding is largely limited to high volatility periods in most markets, we also find evidence of anti-herding mostly during calmer market periods. The prevalence of anti-herding during the low market volatility regime underscores the homogeneous nature of traders in stock markets dominated by retail investors who may seek profits by trading away from the market consensus. Interestingly, however, while anti-herding behavior is prevalent during calm markets, our findings suggest that investors revert towards herding during volatile market periods, underscoring the tendency of investors to feel a sense of security in the majority opinion during periods of uncertainty.

Finally, while the time variation in the level of herding is not found to be correlated with oil return or volatility in the oil-rich GCC stock markets, we observe significant correlations between the level of herding and the speculative ratio in the oil market, suggesting that the oil market's expectations on future oil price movements affect the behavior of traders in local markets of exporting nations. Interestingly, however, we generally observe a positive relation between the degree of speculation and anti-herding regardless of the firm characteristics. We argue that traders in these markets take the speculative signals from the oil market as a sign of positive expectations in oil prices and take advantage of these external signals by trading away from the market consensus in the hope that this will allow them to generate superior profits.

An outline of the remainder of the paper is as follows. Section 2 briefly summarizes the vast literature on investor herds and the oil-stock market nexus, with a focus on emerging markets. Section 3 provides the description of the testing methodology and the data. Section 4 presents the empirical findings and Section 5 concludes the paper.

## 2. Literature review

Herd behavior in financial markets has been a popular topic of interest in both the behavioral finance and asset pricing literature. Numerous studies have tested the presence of herding in different markets and using different methodologies. Bikhchandani and Sharma (2001) define herd behavior as an obvious intent to mimic the actions of other investors and base investment decisions on the actions of more informed traders or the market consensus. Some of the theoretical explanations as to why investors would act in herds include investors' tendency to feel a sense of security in following the crowd (Devenow and Welch, 1996); information acquisition externalities in which investors use resources to acquire new information only if others do (Froot et al, 1992); informational cascades (Banerjee, 2002); reputation (or compensation) related costs of acting differently than others (Maug and Naik, 1996); and the self-reinforcing nature of confidence in the majority opinion (Teraji, 2003).

The traditional studies that examine investor herding include Lakonishok et al. (1992) and Sias (2004) who focus on asset holdings and use the changes in asset positions across investors in herding tests. The holding or transaction based herding measures have been mainly applied to institutional investors in a number of studies including Nofsinger and Sias (1999), Sias (2004), Choi and Sias (2009), Lin and Swanson (2008), and Celiker et al., (2015).[3] On the other hand, a large number of studies have utilized alternative herding tests that are based on return data instead. The return-based herding tests generally examine the cross-sectional behavior of returns across groups of stocks with similar characteristics and base inferences on herding on the pattern of asset returns during alternative market states (Christie and Huang, 1995; Chang et al., 2000; and Hwang and Salmon, 2004). These tests have been applied to different markets in a number of studies including Gleason, et al. (2004), Demirer and Kutan (2006), Tan et al. (2008), Chiang and Zheng (2010), Balcilar et al. (2013, 2014) and more recently, Balcilar and Demirer (2015) and Rahman et al. (2015). Demirer et al. (2010) provides a comparison of the return-based herding tests. These tests generally document evidence of significant investor herding in developing stock markets. As mentioned earlier, however, the literature has largely focused on detecting herding without delving into the underlying drivers of such behavior.

Similarly, the oil-stock market nexus has been examined in numerous contexts in the literature. While the literature has not yet produced theoretical models that relate energy market shocks to risk and return dynamics in stock markets, a large body of empirical studies has shown that oil price shocks can spill over to stock markets, driving risk and return (e.g.

[3] Choi and Sias (2009) provide a review of the herding literature.

Hammoudeh, 2006; Basher and Sadorsky, 2006; Park and Ratti, 2008; Chiou and Lee, 2009; Arouri et. al, 2011; Bouri and Demirer, 2016). Similarly, in applications of asset pricing models, studies including Mohanty et al. (2014) and Demirer et al. (2015) have shown that the sensitivity of a stock to oil price fluctuations can serve as a systematic risk factor even after controlling for market and firm-specific risk factors. Despite the heavy focus on the effect of the oil market on stock return dynamics, however, the channels through which oil price risks spill over to stock markets is still understudied.

In a recent paper that is more related to the topic of the present study, Balcilar et al. (2014) show that a number of global factors, including the price of oil, significantly affect the transition probabilities into market states when herding is present. However, this study ignores the time variation in herding and thus provides an incomplete description of how investor behavior relates to the dynamics of external factors. This is an important consideration for investors and policy makers alike as unexpected shocks in the oil market might lead investors to flock to the same stocks (or industries) by buying (or selling) at the same time, creating excess volatility that eventually leads to bubbles and crashes in these markets. Therefore, the present study contributes to the literature by providing a dynamic analysis of how the time variation in the level of herding in the market relates to speculation and price movements in the oil market. Next, we provide a description of the data and methodology used.

## 3. Data and methodology

### 3.1 Data

We use daily data on all publicly listed firms in five GCC stock exchanges including Saudi Arabia, United Arab Emirates (i.e. Dubai and Abu Dhabi), Kuwait and Qatar for the period between April 4, 2004 and January 27, 2014. The monthly (and daily) stock price, number of shares and book equity data are obtained from Bloomberg. The data on whether a firm comprises a Shariah Board in its corporate structure who oversees the operations of the firm in accordance with Shariah laws is obtained from individual exchanges and company filings. Brent oil price is used to calculate oil returns as most of the exporting countries in the GCC use the price of Brent as a benchmark in pricing their oil types (Demirer et al, 2015). Data on oil price and daily speculative ratio, measured as trading volume divided by open interest, are obtained from Commodity Systems Inc.

Economic characteristics presented in Table 1 underscore the reliance of these economies to energy exports with Saudi Arabia ranking first in global oil exports and all countries carrying high levels of energy exports relative to domestic energy consumption. Industry and services account for over 95% of the GDP in these economies, implying possible sector concentration in their stock markets. Stock market characteristics, on the other hand, suggest greater diversity with Saudi Arabia and Kuwait dominating in terms of listed stocks, while Saudi Arabia stands out in terms of trading activity, indicated by 85% turnover ratio, measured as the total value of shares traded as a percentage of average market capitalization.

### 3.2 Testing methodology

As mentioned earlier, the main advantage of the return-based herding tests, compared to tests based on investors' holding data, is that these tests allow us to capture the dynamic nature of herding as they employ high frequency data and thus can be used to model the time-variation in the level of herding in the market. In this particular study, we employ a testing methodology originally suggested by Christie and Huang (1995), later improved by Chang et al. (2000) and applied to a large number of different markets including U.S. and Asian equities (Chang et al., 2000), exchange traded funds (Gleason et al., 2004), Asian stock markets (Tan et al., 2008; Demirer et al., 2010), global sectors (Chiang and Zheng, 2010), American Depository Receipts (Demirer et al., 2014), Gulf Arab stock markets (Balcilar et al., 2013, 2014; Rahman et al., 2015), and the Turkish stock market (Balcilar and Demirer, 2015), among others. However, as mentioned earlier, these tests have largely focused on detecting the presence of herd behavior in these markets without relating the time-variation in herding to potential underlying factors. Furthermore, most of these studies have utilized static models in their analysis which fail to capture the dynamic nature of herding. Below, we briefly explain the testing procedure for the static benchmark model and the dynamic modification that accommodates the time-variation in herding.

The testing methodology is derived from an asset pricing model that describes returns, in this case the CAPM specification, and interprets deviations from the theoretical model in the context of herding. The use of the CAPM specification as the benchmark model is appropriate in the context of GCC stock markets as Demirer et al. (2015) show that the firm-level risk factors including size and book-to-market ratio that are documented to be significant for U.S. stock returns, are not consistent determinants of stock returns in these developing stock markets. The main focus of the test is the dispersion of asset returns measured by the cross-sectional absolute deviation of returns (CSAD) expressed as

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

where $N$ is the number of firms in the portfolio, $R_{i,t}$ is the observed return on firm $i$ for day $t$ and $R_{m,t}$ is the return on the market portfolio for day $t$. This measure can be regarded as an indicator of directional similarity in asset returns on a given day relative to the market. Following the CAPM specification of returns, one can then show that the derivative of the expected cross-sectional absolute deviation with respect to the expected market return is

$$\frac{\partial E(CSAD_t)}{\partial R_{m,t}} = \frac{1}{N}\sum_{i=1}^{N} | \beta_i - \beta_m | \qquad \textbf{(2)}$$

which is non-negative, implying that the cross-sectional dispersion in asset sensitivities to market return should in theory lead asset returns to display increasingly dissimilar behavior for larger market movements. The second derivative of the CSAD term with respect to market return, on the other hand, is expected to be zero, indicating a linear relationship between asset betas and expected returns – as hypothesized by the CAPM. Noting these expectations based on the underlying theoretical model, Chang et al. (2000) suggest that during periods when herding is present in the market, the linear relation implied by CAPM should no longer hold. Furthermore, as investors engage in correlated actions due to herd behavior, asset returns display greater directional similarity, driven by simultaneous trades in the same direction. As a result, they hypothesize that observing a negative and non-linear relationship between cross-sectional return dispersions and market return will be consistent with the presence of herding in the market. Consequently, they propose the following quadratic model

$$CSAD_t = \alpha_0 + \alpha_1 \left| R_{m,t} \right| + \alpha_2 R_{m,t}^2 + \varepsilon_t \qquad \textbf{(3)}$$

where a significant and negative estimate for $\alpha_2$ is used as support for the presence of herding. As the herding test in Equation (3) is based on the coefficient of the non-linear term, we focus on the herding coefficient ($\alpha_2$) as a proxy for the level of herding in the market so that increasingly negative values for the herding coefficient indicate higher degree of herding.

Considering that herd behavior is a dynamic phenomenon with periods during which herding may or may not occur, the static structure of the benchmark model in Equation (3) fails to capture possible changes in investors' behavior during different market conditions. An optimal way to accommodate the time-variation in the level of herding, in this context, is to allow the parameters of the herding model in Equation (3) to change over time with the use of a time-varying parameter (TVP) model. Furthermore, the evidence in the herding literature suggests that herding is highly related to market regimes and is more prevalent during volatile market periods (e.g. Balcilar et al., 2013, 2014). Therefore, in order to accommodate both the time-variation and structural breaks in our estimations, we propose a Markov switching time-varying parameter (MS-TVP) herding model specified as follows:

$$CSAD_t = \alpha_{0t} + \alpha_{1t}\left|R_{m,t}\right| + \alpha_{2t}R_{m,t}^2 + e_t \quad \textbf{(4a)}$$
$$\alpha_{it} = \alpha_{it-1} + v_{it}, \quad i = 0,1,2 \quad \textbf{(4b)}$$
$$e_t \sim N\left(0, \sigma_{e,s_t}^2\right), \quad S_t \in \{1,2\} \quad \textbf{(4c)}$$
$$v_{it} \sim N(0, \sigma_{vi}^2) \quad \textbf{(4d)}$$

where $N$ denotes the normal distribution and $S_t \in \{1,2\}$ is the latent regime variable following a two-state, first order Markov process that represents normal and hectic market states. The MS-TVP model is specified in a way that all parameters, including the herding coefficient, $\alpha_{2t}$, are allowed to display both regime-specific and time-varying features. This flexibility allows us to track the evolution of herding in the market and also relate to external factors. In matrix notation, the MS-TVP herding model can be written as follows:

$$CSAD_t = X_t\alpha_t + e_t, \quad t = 1,2,\ldots,T \quad \textbf{(5a)}$$
$$\alpha_t = \alpha_{t-1} + v_t \quad \textbf{(5b)}$$
$$e_t \sim N\left(0, \sigma_{e,s_t}^2\right), \quad S_t \in \{1,2\} \quad \textbf{(5c)}$$
$$v_t \sim N(0, Q) \quad \textbf{(5d)}$$
$$\sigma_{e,S_t}^2 = \sigma_{e1}^2(2 - S_t) + \sigma_{e2}^2(S_t - 1), \quad \sigma_{e2}^2 > \sigma_{e1}^2 \quad \textbf{(5e)}$$
$$P[S_t = 1|S_{t-1} = 1] = p_{11}, \quad P[S_t = 2|S_{t-1} = 2] = p_{22} \quad \textbf{(5f)}$$

where $X_t = (1, \left|R_{m,t}\right|, R_{m,t}^2)'$, $\alpha_t = (\alpha_{0t}, \alpha_{1t}, \alpha_{2t})'$, $Q$ is (3×3) diagonal variance matrix, and $p_{ij} = P[S_t = i|S_{t-1} = j]$, $i, j = 1,2,$ is the probability of being in regime $i$ at time $t$ given that the market was in regime $j$ at time $t - 1$ with regimes $i$ and $j$ taking values in {1, 2}. Finally, the transition probabilities satisfy $\sum_{i=1}^{2} p_{ij} = 1$. Note that the condition $\sigma_{e2}^2 > \sigma_{e1}^2$ implies that the second regime (Regime 2) is the high volatility or hectic regime.

Several novelties of the MS-TVP model in Equations (4)-(5) include (i) it endogenously models the time-varying herd behavior by allowing the parameters of the model to stochastically evolve over time; (ii) the well-documented heteroskedasticity feature of financial returns is endogenously modelled via the Markov switching volatility process, allowing the unconditional variance to shift with regime changes; and (iii) it allows the learning process of investors to respond to regime changes. The estimation is done using the maximum likelihood (ML) method based on the Kalman filter that has been applied in different contexts to make inferences on the time-varying coefficient models.[4] An advantage of the Kalman filter is that it allows us to estimate the herding coefficients in a Bayesian fashion as the new information is available in the form of regime shifts or shocks to the market. Therefore, the herding coefficients estimated by the model track both the regime shifts in the market and how investors respond to new information in an optimal way.

## 4. Empirical results

### 4.1 Descriptive statistics

The herding literature generally suggests that herd formation would be more prevalent among traders within sufficiently homogeneous groups in which they face similar decision challenges and it is easier to observe each other's trades (e.g. Christie and Huang, 1995; Chang et al., 2000; Bikhchandani and Sharma, 2001; and Gleason et al., 2004). For this reason, we perform our analyses by grouping stocks based on several characteristics. First, we examine stocks sorted on industry classification by focusing on the three largest industries, i.e. financials, industrials, and consumer cyclicals, based on the industry classification by each exchange. These three industries are selected as (i) industrials and services account for over

[4] See Kim and Nelson (1999) for further details of the estimation procedure.

95% of the GDP in these economies (Table 1); and (ii) these three industries include relatively a higher number of firms compared to the other industries, allowing for a meaningful representation of the cross-sectional behavior of firm returns in our tests. We next sort firms into size groups by assigning stocks to two size portfolios (Big and Small) based on the firm's market value of equity (MVE) relative to the median MVE in December of each year. Finally, we classify firms into conventional and Islamic stock groups based on their compliance with Sharia-based investment rules (data on Sharia compliance is obtained from individual exchanges).

Table 2 provides the summary statistics for daily market index returns and cross-sectional return dispersions for each group. We observe that all GCC exchanges have positive mean returns despite the inclusion of the global financial crisis in the sample period. On the other hand, Dubai, as a hub of real estate investment in the region, experiences the highest volatility in market returns. Examining cross-sectional return dispersions, we observe that financials, small capitalization and conventional stocks generally display the highest dispersion across firm returns, possibly driven by the cross-sectional variation in the sensitivity of these stocks to unexpected news or shocks, either in their markets or globally (particularly for financials). Interestingly, Islamic firms generally display lower return dispersions, suggesting a greater level of directional similarity of returns among these stocks, possibly due to the restrictions on the type of investments that these firms are allowed to undertake.

**4.2 Evidence on herding**

The estimates for the static, benchmark model is presented in Table 3. Consistent with the theoretical expectation described in Equation (2), we generally observe a positive relationship between return dispersions and absolute market return, implied by positive $\alpha_1$

estimates. Examining the herding coefficients however, the static models imply relatively more consistent evidence in support of herding in the case of Saudi Arabia and Qatar. The widespread evidence of herding in Saudi Arabia is in line with Rahman et al. (2015) who note that Saudi traders constitute a homogeneous market clientele and engage in correlated trading regardless of stock characteristics. Interestingly however, the static model does not provide any notable differences across the different firm characteristics, while no evidence of herding is observed for Dubai and Kuwait. As Balcilar et al. (2013) note, the weak evidence of herding observed in static tests may be due to the weakness of the static model in capturing the dynamic nature of herd behavior, thus ignoring the periods (or market states) during which herding may or may not be present.

The weakness of the static model is underscored by the estimates of the MS-TVP model reported in Table 4. The estimates for the regime-specific volatility terms ($\sigma_{ei}$, $i$=1,2) clearly differentiate each market regime in terms of the level of market volatility. In the case of Saudi Arabia, for example, the estimated variance of 0.819% in regime 2 (high volatility) is about four times as high as that of 0.190 for regime 1 (low volatility). Similarly, volatility of small caps in Abu Dhabi is about 8 times as high in regime 2 as in regime 1. Furthermore, examining the regime transition probabilities ($p_{ij}$) reported in the same table, we observe that both regimes are highly persistent indicated by high probability of staying in the same regime. The observed regime properties, therefore, clearly point to the presence of more than one market regime in these stock markets.

The regime-specific features are also emphasized in the plots for the time-varying herding coefficients $\alpha_{2,t}$ presented in Figures 1-5. The gray shaded bands represent the 95% confidence intervals computed using the estimate of the variance of $\alpha_{2,t}$ in Table 4. Note that the estimates for $t = 1, ,2 \ldots ,20$ are excluded since the Kalman filter requires a burn-in period for the parameters to converge. The vertical shades (in light green) mark the high volatility regime (Regime 2) determined based on the maximum of the smoothed regime probabilities.[5] Examining the periods that are marked by the vertical shades, we see that the high volatility regime largely corresponds to the oil price boom period around 2006 into 2007 for the heavy exporters of Saudi Arabia and Kuwait; this is the period when the price of oil hit all-time highs before the oil market crashed in mid to late-2008. We also observe that most markets switch to the high volatility regime during the global financial crisis period, particularly in the case of financial stocks, suggesting possible contagion of the credit market uncertainty to financial firms worldwide.

Focusing on the herding coefficients, the MS-TVP model yields highly time-varying estimates, suggesting that the level of herding in these markets indeed exhibits a dynamic pattern in which the market switches between herding and anti-herding.[6] The time-variation in the herding coefficients is also evident in the estimated standard deviations ($\sigma_{v2}$) for the error term ($v_{2t}$) of the herding coefficient in Equation 5. We generally observe greater variability in the herding coefficients in the case of financials and conventional stocks and for Saudi Arabia, implying greater likelihood of more frequent switches between herding and anti-herding among investors in these markets.

Interestingly, while the static model described earlier did not detect any herding in Kuwait and Dubai (Table 3), Figures 3 and 4 clearly suggest that these markets in fact experienced herding during the pre-2006 when the real estate market in Dubai and the oil

[5] The detailed plots for the smoothed probabilities for the low and high probability regimes are not provided for brevity, but are available upon request.
[6] Babalos and Stavroyiannis (2015) define anti-herding as positive herding when investors trade away from the market consensus or run contrary to the crowd.

market were booming. In Saudi Arabia, however, herding is largely limited to high volatility periods that correspond to the global financial crisis when the herding coefficients fall into the negative territory. We also observe that the Saudi market, particularly for large caps and Islamic stocks, exhibits more frequent switches between herding and anti-herding. Pierdzioch et al. (2010) document evidence of anti-herding among oil price forecasters, arguing that professional forecasters deliberately place their forecasts away from the cross-sectional consensus forecast. Considering that the Saudi market is the dominant exchange in the GCC in terms of size and stock turnover (Table 1), the presence of larger number of traders in this market may diminish the advantage of uncovering new information, thus incentivizing investors to follow others' trades instead. It is, however, interesting that these markets also experience long periods of anti-herding, implied by positive and significant herding coefficient estimates. The prevalence of anti-herding, largely during the low market volatility regime, underscores the domination of retail investors in these markets which makes it hard to win when one's trades are similar to others (Naujoks et al., 2009). It can also be argued that the homogeneous nature of Saudi traders as Rahman et al (2015) note drives these investors to seek profits by trading away from the market consensus; however, this behavior reverts towards herding during volatile (or crisis) market periods as observed in Figure 1.

### 4.3 Oil market dynamics and herding

As explained earlier, the heavy dependence of these economies on energy exports coupled with limited market depth and diversification opportunities available domestically can expose investors' to unhedged oil price risks in their portfolios. This risk exposure, in turn, can make investors' trading behavior particularly sensitive to oil market dynamics and contribute to herd behavior as they may overreact to common information signals or recent news regarding the oil market. Therefore, in the next step, we relate the estimated time-varying herding coefficients to oil market factors. An obvious factor is the oil return and return volatility that can be expected to affect stock market dynamics as a number of papers in the literature have already documented (e.g. Chiou and Lee, 2009; Arouri et. al, 2011; Bouri and Demirer, 2016).

Another factor is the speculation in the oil market and for this purpose, we use the speculative ratio recently suggested by Chan et al. (2015). The speculative ratio for a given trading day is defined as the trading volume divided by open interest and can be regarded as a measure of the extent of speculative activity relative to hedging activity on a given trading day. Chan et al. (2015) argue that a lower ratio of trading volume to open interest implies lower speculative activity relative to hedging as hedgers would be more likely to obtain more long positions in the futures market if they see a potential positive price movement in order to better cover their underlying positions. This, in turn, would lead to a large increase in open interest relative to trading volume, thus yielding a lower speculative ratio. Since the market's expectations on global oil price movements are best reflected in futures market transactions, we use data on trading volume and open interest for the nearby Brent oil futures contracts traded on the Chicago Mercantile Exchange and calculate the daily speculative ratio values for the oil market.

Table 5 presents the Pearson correlation coefficients of the time-varying herding estimates ($\alpha_{2,t}$) with Brent oil returns and the oil market speculative ratio.[7] Interestingly, we do not observe a significant relationship between oil price movements and the level of herding in these markets, implied by insignificant correlation estimates. On the other hand, significant correlations are observed with the speculative ratio, suggesting that market's expectations on

[7] Correlations with oil return volatility yield qualitatively similar results as oil returns and are not reported for brevity.

future price movements implied by this ratio, can have explanatory power in these oil-sensitive stock markets. However, the correlations between the estimated herding coefficients and the speculative ratio are found to be largely positive, implying that higher level of speculative activity in the oil market is associated with anti-herding behavior in these markets. The positive relation between the degree of speculation and anti-herding is observed in most markets regardless of the firm characteristics and is particularly strong in Saudi Arabia and Qatar.

Following the evidence of anti-herding among oil price forecasters (Pierdzioch et al., 2010) and among stock market analysts (Naujoks et al., 2009) and the evidence presented in Section 4.2, we argue that traders in these markets take the speculative signals from the oil market as a sign of positive movements in oil prices and take advantage of the speculative signals by trading away from the market consensus in the hope that they will generate superior profits. Overall, the proposed MS-TVP model which allows for time-variation in the level of herding in the market yields a number of interesting findings that are not possible to capture in a static specification. It is also interesting that it is not necessarily the actual price movements in the oil market, but rather, the oil market's expectations reflected by the speculative ratio that are more significantly related to herd behavior in these stock markets.

## 5. Conclusions

This paper examines the time-variation in the level of herding in a stock market by proposing a Markov switching time-varying parameter (MS-TVP) herding model. We examine investor herding in a dynamic context which accommodates not only the different market regimes when herding may or may not be present, but also the time-variation in herding coefficients. Using firm-level data from the oil-rich Gulf Arab stock markets dominated by retail investors who are argued to be less informed, trade for non-informational reasons (Hirose et al., 2009) and possibly exhibit greater herding tendencies, we then relate the level of herding in the market to the time variation in oil market dynamics. By doing so, this study contributes to our understanding of how herd behavior in a stock market evolves over time and how external factors may play a role in affecting investor behavior.

Our findings show that the level of herding indeed exhibits a dynamic pattern in which the market switches between herding and anti-herding, more frequently in the case of investors trading large cap and Islamic stocks. While investor herding is largely limited to high volatility periods in most markets, we also find evidence of anti-herding mostly during calmer market periods. While anti-herding behavior is prevalent during calm markets, we observe that investors revert towards herding during volatile market periods, underscoring the tendency of investors to feel a sense of security in the majority opinion during periods of uncertainty.

Finally, while the time variation in the level of herding is not found to be correlated with oil return or volatility, we observe significant correlations between the level of herding in domestic stock markets and the speculative activity in the global oil market, suggesting that the oil market's expectations on future oil price movements can affect the behavior of traders in these energy sensitive stock markets. We argue that traders in these markets take the speculative signals from the oil market as a sign of positive expectations in oil prices and take advantage of these signals by trading away from the market consensus in the hope that this will allow them to generate superior profits.

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**Table 1**. Stock market and economic characteristics.

| | S. Arabia | UAE | Kuwait | Qatar |
|---|---|---|---|---|
| Oil exports global rank | 1 | 3 | 6 | 22 |
| Energy exports (% of energy use) | 212 | 188 | 401 | 484 |
| Composition of GDP: | | | | |
| Agriculture | 1.9% | 0.7% | 0.4% | 0.1% |
| Industry | 57% | 55.1% | 60.6% | 68% |
| Services | 41.1% | 44.3% | 39% | 32.1% |
| Number of listed firms | 158 | 102 | 189 | 42 |
| Market capitalization (% of GDP) | 51 | 18 | 56 | 67 |
| Turnover Ratio (%) | 85 | 16 | 19 | 19 |

**Note:** The stock market data are compiled from Mansur and Delgado (2008) and the World Bank database (2012). The economic data are obtained from the CIA World Factbook (2014). Turnover ratio is the total value of shares traded during the period divided by the average market capitalization for the period.

**Table 2.** Summary Statistics: Stock Market Returns and Cross-Sectional Absolute Deviations.

| | $R_m$ | **Return Dispersions (Cross-sectional absolute deviation)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | All Stocks | Financials | Industrials | Consumer Cyclical | Small | Big | Conventional | Islamic |
| | | | | | **Saudi Arabia** | | | | |
| Mean | 0.01% | 1.61% | 1.58% | 1.68% | 1.34% | 1.62% | 1.11% | 1.54% | 1.74% |
| Std. Dev. | 1.55% | 0.76% | 0.87% | 1.00% | 0.76% | 0.78% | 0.61% | 0.77% | 1.71% |
| Min. | -10.10% | 0.11% | 0.04% | 0.31% | 0.05% | 0.06% | 0.05% | 0.11% | 0.01% |
| Max. | 9.05% | 6.72% | 8.10% | 17.50% | 9.18% | 7.36% | 5.47% | 6.77% | 44.72% |
| | | | | | **Abu Dhabi** | | | | |
| Mean | 0.03% | 2.40% | 2.93% | 2.24% | 2.31% | 2.69% | 1.35% | 2.48% | 2.04% |
| Std. Dev. | 1.26% | 0.94% | 2.71% | 0.90% | 1.68% | 1.92% | 0.77% | 1.96% | 1.54% |
| Min. | -8.65% | 0.81% | 0.07% | 0.20% | 0.21% | 0.30% | 0.02% | 0.15% | 0.22% |
| Max. | 8.25% | 15.48% | 75.41% | 10.38% | 30.17% | 73.89% | 9.12% | 79.95% | 40.14% |
| | | | | | **Dubai** | | | | |
| Mean | 0.03% | 1.66% | 1.79% | 1.33% | | 1.86% | 1.34% | 1.83% | 1.63% |
| Std. Dev. | 1.84% | 0.80% | 1.00% | 0.99% | | 1.07% | 1.21% | 1.16% | 1.51% |
| Min. | -12.16% | 0.23% | 0.16% | 0.06% | | 0.16% | 0.01% | 0.01% | 0.08% |
| Max. | 10.22% | 10.61% | 16.81% | 10.48% | | 13.21% | 23.81% | 9.84% | 37.86% |
| | | | | | **Kuwait** | | | | |
| Mean | 0.01% | 2.43% | 2.53% | 2.36% | 2.25% | 2.57% | 1.77% | 2.45% | 2.32% |
| Std. Dev. | 0.79% | 0.50% | 0.89% | 0.58% | 0.74% | 0.56% | 0.56% | 0.51% | 0.68% |
| Min. | -4.04% | 0.76% | 0.17% | 0.61% | 0.25% | 0.12% | 0.18% | 0.73% | 0.12% |
| Max. | 3.80% | 4.50% | 15.42% | 4.60% | 8.96% | 5.02% | 5.40% | 5.42% | 5.95% |
| | | | | | **Qatar** | | | | |
| Mean | 0.02% | 1.39% | 1.70% | 1.37% | 1.11% | 1.48% | 1.05% | 1.40% | 1.27% |
| Std. Dev. | 1.47% | 0.80% | 2.48% | 0.75% | 0.88% | 1.01% | 0.84% | 0.99% | 0.87% |
| Min. | -9.16% | 0.31% | 0.04% | 0.04% | 0.01% | 0.41% | 0.10% | 0.38% | 0.01% |
| Max. | 9.42% | 25.06% | 94.26% | 13.44% | 18.95% | 29.11% | 16.52% | 29.09% | 15.46% |

**Note:** The first column (shaded) for each market reports the summary statistics for stock market index returns ($R_m$). Data for the Consumer Cyclical industry for Dubai is not available.

**Table 3.** Estimates of the static herding models.

| | All Stocks | Cons. Cyc. | Financials | Industrials | Small | Big | Conventional | Islamic |
|---|---|---|---|---|---|---|---|---|
| | | | | **Saudi Arabia** | | | | |
| $\alpha_0$ | 1.2646*** | 1.2673*** | 1.4002*** | 1.0361*** | 1.3342*** | 0.8218*** | 1.1862*** | 1.5986*** |
| | (0.0234) | (0.0261) | (0.0390) | (0.0232) | (0.0254) | (0.0192) | (0.0230) | (0.0748) |
| $\alpha_1$ | 0.5085*** | 0.4793*** | 0.3757*** | 0.4436*** | 0.4450*** | 0.3753*** | 0.5079*** | 0.1931** |
| | (0.0338) | (0.0375) | (0.0459) | (0.0365) | (0.0373) | (0.0309) | (0.0326) | (0.0757) |
| $\alpha_2$ | -0.0551*** | -0.0598*** | -0.0316*** | -0.0467*** | -0.0538*** | -0.0256*** | -0.0553*** | -0.0175 |
| | (0.0050) | (0.0054) | (0.0079) | (0.0069) | (0.0060) | (0.0056) | (0.0047) | (0.0129) |
| RSS | 992.9824 | 1408.5339 | 1904.6711 | 1022.5746 | 1052.0724 | 555.2224 | 1058.0681 | 6112.5046 |
| log L | -2166.3762 | -2524.8825 | -2834.3373 | -2196.4909 | -2149.3318 | -1534.471 | -2261.7312 | -4105.9485 |
| | | | | **Abu Dhabi** | | | | |
| $\alpha_0$ | 2.1949*** | 2.7430*** | 2.0510*** | 2.1225*** | 2.4833*** | 1.0055*** | 2.2289*** | 1.7826*** |
| | (0.0476) | (0.0816) | (0.0517) | (0.0937) | (0.0498) | (0.0238) | (0.0514) | (0.0409) |
| $\alpha_1$ | 0.2810*** | 0.2661 | 0.2494*** | 0.2607* | 0.3059*** | 0.5288*** | 0.3773*** | 0.3952*** |
| | (0.0813) | (0.1623) | (0.0843) | (0.1434) | (0.0659) | (0.0443) | (0.0528) | (0.0817) |
| $\alpha_2$ | -0.0277 | -0.0292 | -0.0244 | -0.0309 | -0.0263** | -0.0461*** | -0.0323*** | -0.0342** |
| | (0.0183) | (0.0327) | (0.0208) | (0.0223) | (0.0126) | (0.0100) | (0.0108) | (0.0141) |
| RSS | 902.0175 | 7662.4867 | 825.9721 | 2929.7709 | 8456.7038 | 1136.4346 | 8752.0429 | 5322.9452 |
| log L | -1409.2887 | -2531.4344 | -1363.0944 | -2027.1736 | -4775.0374 | -2457.8824 | -4822.5919 | -4247.2616 |
| | | | | **Dubai** | | | | |
| $\alpha_0$ | 1.4467*** | | 1.5840*** | 1.1322*** | 1.6587*** | 0.9762*** | 1.6134*** | 1.3677*** |
| | (0.0362) | | (0.0475) | (0.0408) | (0.0388) | (0.0495) | (0.0415) | (0.0628) |
| $\alpha_1$ | 0.1766*** | | 0.1696*** | 0.1874*** | 0.1729*** | 0.2906*** | 0.1430*** | 0.2291*** |
| | (0.0379) | | (0.0448) | (0.0486) | (0.0399) | (0.0512) | (0.0455) | (0.0504) |
| $\alpha_2$ | 0.0017 | | 0.0018 | -0.0076 | -0.0023 | 0.0030 | 0.0124 | -0.0065 |
| | (0.0061) | | (0.0066) | (0.0091) | (0.0068) | (0.0086) | (0.0076) | (0.0083) |
| RSS | 989.7687 | | 1609.9192 | 1609.8962 | 2503.6811 | 2946.6873 | 2800.4961 | 4960.2756 |
| log L | -1949.174 | | -2361.4556 | -2361.4435 | -3343.7997 | -3529.6908 | -3428.5415 | -4068.806 |
| | | | | **Kuwait** | | | | |
| $\alpha_0$ | 2.4985*** | 2.4995*** | 2.4439*** | 2.1795*** | 2.6426*** | 1.7465*** | 2.5121*** | 2.3660*** |
| | (0.0205) | (0.0388) | (0.0240) | (0.0304) | (0.0210) | (0.0207) | (0.0190) | (0.0254) |
| $\alpha_1$ | -0.1997*** | 0.0825 | -0.2406*** | 0.1632** | -0.2113*** | 0.0365 | -0.1767*** | -0.1410** |
| | (0.0573) | (0.0966) | (0.0636) | (0.0778) | (0.0547) | (0.0515) | (0.0498) | (0.0648) |
| $\alpha_2$ | 0.0624*** | -0.0194 | 0.0736*** | -0.0290 | 0.0638*** | 0.0000 | 0.0547*** | 0.0448* |
| | (0.0232) | (0.0368) | (0.0247) | (0.0287) | (0.0200) | (0.0176) | (0.0182) | (0.0240) |
| RSS | 434.1847 | 1356.2719 | 574.344 | 944.302 | 618.7705 | 629.9896 | 524.2269 | 926.8394 |
| log L | -1257.6104 | -2239.4498 | -1498.7621 | -1927.3636 | -1669.0086 | -1687.0943 | -1504.8143 | -2081.5082 |
| | | | | **Qatar** | | | | |
| $\alpha_0$ | 1.1703*** | 1.5982*** | 1.1532*** | 0.9376*** | 1.3107*** | 0.7590*** | 1.1795*** | 1.0625*** |
| | (0.0196) | (0.0424) | (0.0254) | (0.0276) | (0.0261) | (0.0218) | (0.0246) | (0.0246) |
| $\alpha_1$ | 0.3174*** | 0.1584* | 0.3084*** | 0.2351*** | 0.2418*** | 0.4063*** | 0.2958*** | 0.3084*** |
| | (0.0307) | (0.0875) | (0.0305) | (0.0398) | (0.0298) | (0.0266) | (0.0281) | (0.0304) |
| $\alpha_2$ | -0.0323*** | -0.0199 | -0.0330*** | -0.0213*** | -0.0223*** | -0.0358*** | -0.0267*** | -0.0362*** |
| | (0.0055) | (0.0158) | (0.0052) | (0.0071) | (0.0049) | (0.0045) | (0.0049) | (0.0046) |
| RSS | 1003.241 | 10332.602 | 873.3923 | 1254.626 | 2210.2337 | 1386.5483 | 2100.1772 | 1620.0754 |
| log L | -1952.0697 | -3913.3392 | -1835.5019 | -2140.1188 | -3150.646 | -2631.6754 | -3129.213 | -2835.1439 |

**Note:** The table reports the estimates for the static (benchmark) herding model shown in Equation (3) for the period April 4, 2004 and January 27, 2014. Data for consumer cyclicals for Dubai is not available. Herding coefficients are indicated in shaded rows; negative and significant values imply the presence of herding in the market. All estimations are done using the Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. Log L is the log likelihood of the estimated model. The numbers in parentheses are the standard errors. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

**Table 4.** Estimates of the MS-TVP herding models.

| | All Stocks | Cons. Cyc. | Financials | Industrials | Small | Big | Conventional | Islamic |
|---|---|---|---|---|---|---|---|---|
| | | | | **Saudi Arabia** | | | | |
| $\sigma_{v0}$ | 0.07681 | 0.13808 | 0.07150 | 0.07864 | 0.08631 | 0.05909 | 0.07878 | 0.13295 |
| | (0.00056) | (0.00227) | (0.00085) | (0.00080) | (0.00066) | (0.00065) | (0.00061) | (0.00104) |
| $\sigma_{v1}$ | 0.00753 | 0.00013 | 0.00342 | 0.00718 | 0.01004 | 0.00957 | 0.00561 | 0.00000 |
| | (0.00037) | (0.00004) | (0.00036) | (0.00047) | (0.00035) | (0.00053) | (0.00026) | (0.00040) |
| $\sigma_{v2}$ | 0.00585 | 0.00000 | 0.00176 | 0.00455 | 0.00274 | 0.00601 | 0.00644 | 0.00489 |
| | (0.00016) | (0.00006) | (0.00008) | (0.00019) | (0.00017) | (0.00012) | (0.00017) | (0.00021) |
| $\sigma_{e1}$ | 0.19042 | 0.81443 | 0.32287 | 0.26603 | 0.21495 | 0.20281 | 0.17066 | 0.34593 |
| | (0.00077) | (0.00303) | (0.00138) | (0.00161) | (0.00086) | (0.00092) | (0.00066) | (0.00134) |
| $\sigma_{e2}$ | 0.81964 | 2.46036 | 0.88134 | 0.82205 | 0.90433 | 0.60805 | 0.75594 | 1.13798 |
| | (0.00437) | (0.05026) | (0.00648) | (0.00591) | (0.00482) | (0.00474) | (0.00363) | (0.00489) |
| $p_{11}$ | 0.95986 | 0.98570 | 0.94506 | 0.95576 | 0.96426 | 0.95546 | 0.96119 | 0.96090 |
| | (0.00079) | (0.00070) | (0.00149) | (0.00111) | (0.00073) | (0.00099) | (0.00069) | (0.00097) |
| $p_{22}$ | 0.86559 | 0.77087 | 0.77100 | 0.87924 | 0.86470 | 0.87943 | 0.89148 | 0.93088 |
| | (0.00259) | (0.00820) | (0.00593) | (0.00275) | (0.00255) | (0.00417) | (0.00209) | (0.00202) |
| log L | -835.585 | -2354.325 | -1145.17 | -1306.494 | -924.132 | -712.253 | -781.625 | -2186.001 |
| | | | | **Abu Dhabi** | | | | |
| $\sigma_{v0}$ | 0.08422 | 0.07436 | 0.07678 | 0.09409 | 0.09092 | 0.05846 | 0.10042 | 0.11195 |
| | (0.00115) | (0.00264) | (0.00078) | (0.00093) | (0.00099) | (0.00074) | (0.00131) | (0.00131) |
| $\sigma_{v1}$ | 0.00000 | 0.00000 | 0.00818 | 0.00271 | 0.00197 | 0.00000 | 0.00588 | 0.00241 |
| | (0.00023) | (0.00039) | (0.00029) | (0.00018) | (0.00022) | (0.00023) | (0.00032) | (0.00036) |
| $\sigma_{v2}$ | 0.00054 | 0.00000 | 0.00389 | 0.00253 | 0.00101 | 0.00306 | 0.00169 | 0.00073 |
| | (0.00005) | (0.00008) | (0.00014) | (0.00008) | (0.00006) | (0.00018) | (0.00008) | (0.00006) |
| $\sigma_{e1}$ | 0.44268 | 1.27554 | 0.23604 | 0.28432 | 0.70074 | 0.36570 | 0.74753 | 0.59969 |
| | (0.00164) | (0.00371) | (0.00104) | (0.00114) | (0.00126) | (0.00137) | (0.00139) | (0.00135) |
| $\sigma_{e2}$ | 1.21294 | 4.91054 | 0.91230 | 1.02376 | 5.50227 | 0.95760 | 5.83779 | 2.55948 |
| | (0.01561) | (0.08571) | (0.00370) | (0.00543) | (0.09857) | (0.00519) | (0.11189) | (0.02383) |
| $p_{11}$ | 0.97145 | 0.98537 | 0.95183 | 0.93637 | 0.99431 | 0.93381 | 0.99442 | 0.99249 |
| | (0.00115) | (0.00064) | (0.00086) | (0.00101) | (0.00021) | (0.00129) | (0.00021) | (0.00029) |
| $p_{22}$ | 0.75063 | 0.49644 | 0.90882 | 0.79871 | 0.44090 | 0.80237 | 0.32381 | 0.85849 |
| | (0.01225) | (0.00009) | (0.00181) | (0.00334) | (0.01676) | (0.00425) | (0.01531) | (0.00519) |
| log L | -914.123 | -1871.376 | -1433.671 | -1531.324 | -2731.861 | -1921.644 | -2885.659 | -2570.295 |
| | | | | **Dubai** | | | | |
| $\sigma_{v0}$ | 0.11153 | | 0.08921 | 0.09611 | 0.13789 | 0.06143 | 0.11714 | 0.09802 |
| | (0.00139) | | (0.00153) | (0.00181) | (0.00145) | (0.00076) | (0.00134) | (0.00117) |
| $\sigma_{v1}$ | 0.00281 | | 0.00000 | 0.00000 | 0.00434 | 0.00000 | 0.00611 | 0.00513 |
| | (0.00040) | | (0.00108) | (0.00043) | (0.00034) | (0.00025) | (0.00028) | (0.00032) |
| $\sigma_{v2}$ | 0.00147 | | 0.00704 | 0.00000 | 0.00150 | 0.00414 | 0.00018 | 0.00247 |
| | (0.00009) | | (0.00027) | (0.00006) | (0.00007) | (0.00012) | (0.00007) | (0.00008) |
| $\sigma_{e1}$ | 0.34313 | | 0.53935 | 0.75943 | 0.46621 | 0.38501 | 0.63079 | 0.43853 |
| | (0.00136) | | (0.00324) | (0.00337) | (0.00177) | (0.00103) | (0.00200) | (0.00139) |
| $\sigma_{e2}$ | 0.83218 | | 0.95542 | 1.48550 | 1.31021 | 1.69159 | 1.59227 | 2.32236 |
| | (0.00480) | | (0.00754) | (0.00943) | (0.00698) | (0.00778) | (0.00816) | (0.01329) |
| $p_{11}$ | 0.97121 | | 0.96494 | 0.98968 | 0.96621 | 0.95242 | 0.96204 | 0.94620 |
| | (0.00092) | | (0.00134) | (0.00072) | (0.00077) | (0.00072) | (0.00081) | (0.00043) |
| $p_{22}$ | 0.92909 | | 0.93570 | 0.98634 | 0.90774 | 0.79369 | 0.87847 | 0.52624 |
| | (0.00261) | | (0.00306) | (0.00136) | (0.00243) | (0.00337) | (0.00259) | (0.00064) |
| log L | -1372.495 | | -1196.113 | -1571.019 | -2606.834 | -2190.051 | -3004.171 | -2276.097 |
| | | | | **Kuwait** | | | | |
| $\sigma_{v0}$ | 0.06882 | 0.11933 | 0.07186 | 0.08214 | 0.06906 | 0.05360 | 0.06384 | 0.08874 |
| | (0.00061) | (0.00149) | (0.00100) | (0.00097) | (0.00059) | (0.00075) | (0.00057) | (0.00082) |
| $\sigma_{v1}$ | 0.01073 | 0.00000 | 0.00000 | 0.00000 | 0.00585 | 0.00845 | 0.01147 | 0.00154 |
| | (0.00045) | (0.00023) | (0.00021) | (0.00032) | (0.00032) | (0.00041) | (0.00036) | (0.00063) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $\sigma_{v2}$ | 0.00336 | 0.00085 | 0.00262 | 0.00175 | 0.00243 | 0.00000 | 0.00369 | 0.00311 |
| | (0.00013) | (0.00006) | (0.00010) | (0.00015) | (0.00011) | (0.01792) | (0.00017) | (0.00013) |
| $\sigma_{e1}$ | 0.23687 | 0.41716 | 0.43839 | 0.43105 | 0.27423 | 0.33047 | 0.31458 | 0.41406 |
| | (0.00086) | (0.00180) | (0.00182) | (0.00471) | (0.00087) | (0.00197) | (0.00070) | (0.00128) |
| $\sigma_{e2}$ | 0.31739 | 0.96289 | 1.46673 | 0.67926 | 0.39447 | 0.54275 | 0.05811 | 0.55552 |
| | (0.00122) | (0.00494) | (0.00965) | (0.00457) | (0.00144) | (0.00237) | (0.00377) | (0.00140) |
| $p_{11}$ | 0.99623 | 0.95287 | 0.92005 | 0.90811 | 0.99696 | 0.92355 | 0.98410 | 0.99609 |
| | (0.00031) | (0.00154) | (0.00165) | (0.00689) | (0.00021) | (0.00438) | (0.00074) | (0.00026) |
| $p_{22}$ | 0.99613 | 0.92215 | 0.77013 | 0.93959 | 0.99664 | 0.92782 | 0.77753 | 0.99695 |
| | (0.00033) | (0.00317) | (0.00622) | (0.00648) | (0.00027) | (0.00433) | (0.00672) | (0.00020) |
| | | | | **Qatar** | | | | |
| $\sigma_{v0}$ | 0.08695 | 0.06868 | 0.08958 | 0.05354 | 0.10104 | 0.06368 | 0.08623 | 0.11177 |
| | (0.00079) | (0.00089) | (0.00083) | (0.00094) | (0.00090) | (0.00062) | (0.00072) | (0.00091) |
| $\sigma_{v1}$ | 0.00000 | 0.00278 | 0.00666 | 0.00000 | 0.00000 | 0.00163 | 0.00184 | 0.00489 |
| | (0.00016) | (0.00048) | (0.00046) | (0.00042) | (0.00017) | (0.00022) | (0.00032) | (0.00032) |
| $\sigma_{v2}$ | 0.00111 | 0.00000 | 0.00297 | 0.00228 | 0.00174 | 0.00070 | 0.00233 | 0.00212 |
| | (0.00004) | (0.00019) | (0.00014) | (0.00012) | (0.00006) | (0.00006) | (0.00007) | (0.00009) |
| $\sigma_{e1}$ | 0.25345 | 0.56307 | 0.30287 | 0.36154 | 0.32788 | 0.23263 | 0.27254 | 0.33473 |
| | (0.00078) | (0.00191) | (0.00125) | (0.00131) | (0.00082) | (0.00086) | (0.00078) | (0.00184) |
| $\sigma_{e2}$ | 0.77289 | 0.86980 | 0.43328 | 1.01270 | 1.02273 | 0.82203 | 0.83460 | 0.95958 |
| | (0.00529) | (0.00351) | (0.00196) | (0.00474) | (0.00829) | (0.00397) | (0.00584) | (0.00498) |
| $p_{11}$ | 0.98242 | 0.98403 | 0.98856 | 0.94127 | 0.98564 | 0.95426 | 0.97790 | 0.90593 |
| | (0.00052) | (0.00062) | (0.00085) | (0.00132) | (0.00044) | (0.00087) | (0.00056) | (0.00143) |
| $p_{22}$ | 0.89898 | 0.97728 | 0.98708 | 0.89711 | 0.84439 | 0.90451 | 0.83968 | 0.84307 |
| | (0.00314) | (0.00097) | (0.00107) | (0.00293) | (0.00421) | (0.00246) | (0.00379) | (0.00348) |
| log L | -727.669 | -1917.037 | -941.76 | -1597.791 | -1340.334 | -1307.634 | -1078.942 | -2213.629 |

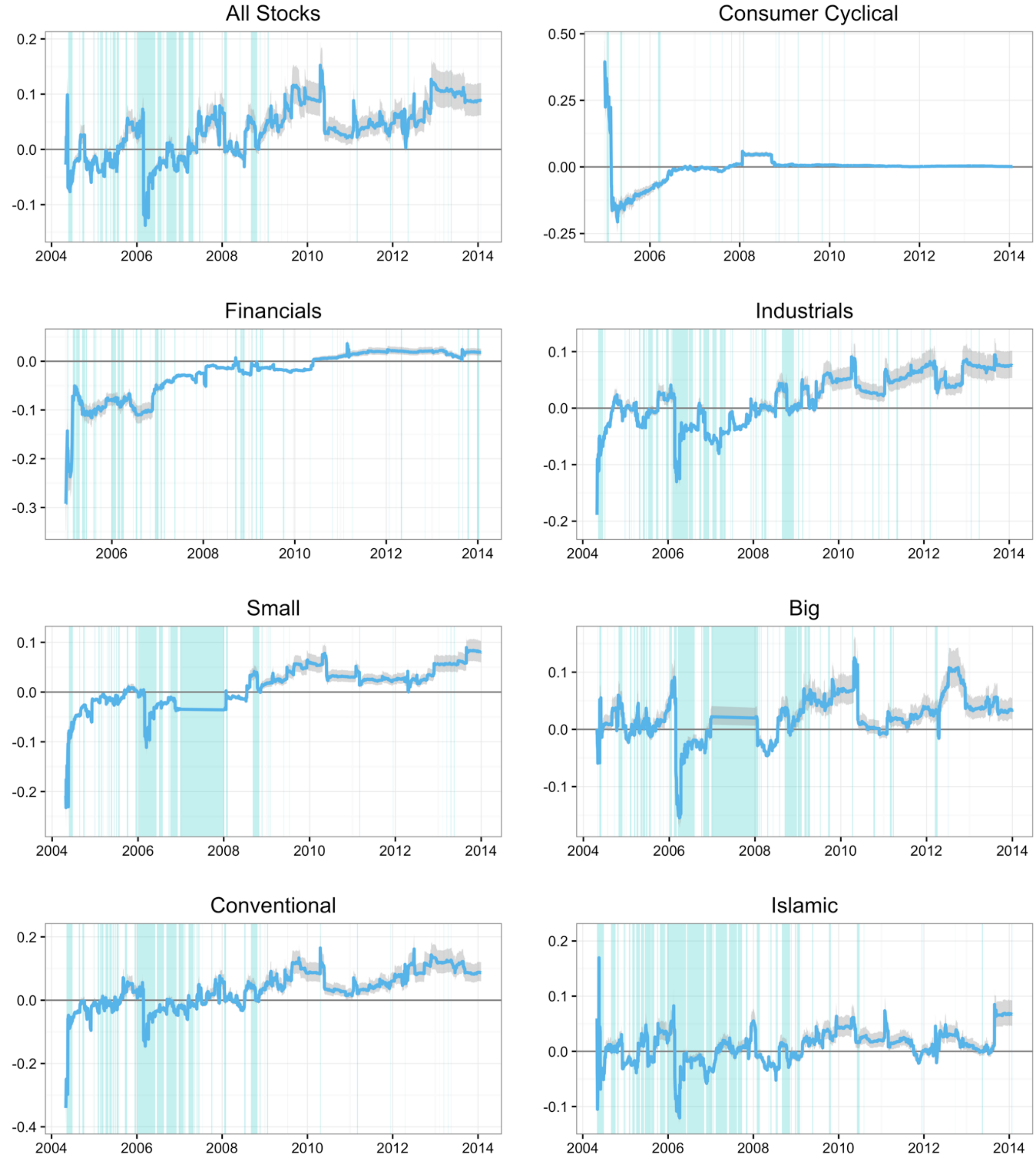
**Note:** The table reports the estimates for the MS-TVP herding model shown in Equations (4)-(5) for the period April 4, 2004 and January 27, 2014. $\sigma_{vi}$ (*i*=0,1,2) is the standard deviation of the error term ( $v_{it}$ ) in Equation 5. $\sigma_{ei}$ (*i*=1,2) is the regime-specific volatility estimate and $p_{ij}$ is the transition probability from regime *i* in period *t-1* to regime *j* in period *t*. Data for consumer cyclicals for Dubai is not available. All estimates are obtained using the Maximum Likelihood (ML) method based on the Kalman filter. Log L is the log likelihood of the estimated model. The numbers in parentheses are the standard errors.

**Table 5.** Correlation of time varying herding estimates with oil market factors.

| | All Stocks | Cons. Cyc. | Financials | Industrials | Small | Big | Conventional | Islamic |
|---|---|---|---|---|---|---|---|---|
| | | | | **Saudi Arabia** | | | | |
| Oil Returns | -0.021 | -0.055** | -0.003 | -0.034 | 0.073216 | -0.044 | -0.031 | -0.031 |
| | (-0.827) | (-2.215) | (-0.109) | (-1.332) | | (-1.632) | (-1.195) | (-1.215) |
| Speculative | 0.220*** | 0.171*** | 0.350*** | 0.307*** | 0.255*** | 0.105*** | 0.240*** | 0.104*** |
| ratio | (8.908) | (7.039) | (15.117) | (12.738) | (9.868) | (3.963) | (9.660) | (4.092) |
| | | | | **Abu Dhabi** | | | | |
| Oil Returns | 0.003 | 0.013 | -0.037 | -0.028 | -0.024 | -0.008 | -0.019 | -0.014 |
| | (0.109) | (0.420) | (-1.456) | (-1.097) | (-1.046) | (-0.336) | (-0.798) | (-0.586) |
| Speculative | 0.018 | -0.259*** | 0.341*** | 0.085*** | -0.224*** | -0.243*** | -0.187*** | -0.098*** |
| ratio | (0.563) | (-8.521) | (14.290) | (3.365) | (-9.868) | (-10.748) | (-8.193) | (-4.232) |
| | | | | **Dubai** | | | | |
| Oil Returns | -0.008 | | -0.019 | 0.011 | -0.006 | 0.025 | -0.017 | -0.022 |
| | (-0.333) | | (-0.600) | (0.360) | (-0.273) | (1.064) | (-0.721) | (-0.915) |
| Speculative | 0.052** | | 0.177*** | 0.118*** | 0.108*** | -0.091*** | -0.099*** | 0.206*** |
| ratio | (2.106) | | (5.732) | (3.767) | (4.627) | (-3.889) | (-4.195) | (8.890) |
| | | | | **Kuwait** | | | | |
| Oil Returns | 0.002 | -0.008 | -0.024 | 0.029 | 0.002 | 0.003 | -0.003 | -0.007 |
| | (0.075) | (-0.307) | (-0.992) | (1.195) | (0.095) | (0.124) | (-0.114) | (-0.279) |
| Speculative | 0.175*** | -0.107*** | 0.099*** | -0.155*** | 0.162*** | 0.185*** | 0.234*** | 0.116*** |
| ratio | (7.267) | (-4.373) | (4.047) | (-6.412) | (6.731) | (7.718) | (9.883) | (4.812) |
| | | | | **Qatar** | | | | |
| Oil Returns | -0.024 | 0.011 | 0.010 | -0.009 | -0.028 | -0.004 | -0.022 | -0.004 |
| | (-0.953) | (0.436) | (0.417) | (-0.363) | (-1.183) | (-0.149) | (-0.928) | (-0.183) |
| Speculative | 0.304*** | 0.196*** | 0.205*** | 0.348*** | 0.131*** | 0.368*** | 0.267*** | 0.347*** |
| ratio | (12.918) | (8.199) | (8.586) | (15.033) | (5.592) | (16.745) | (11.838) | (15.782) |

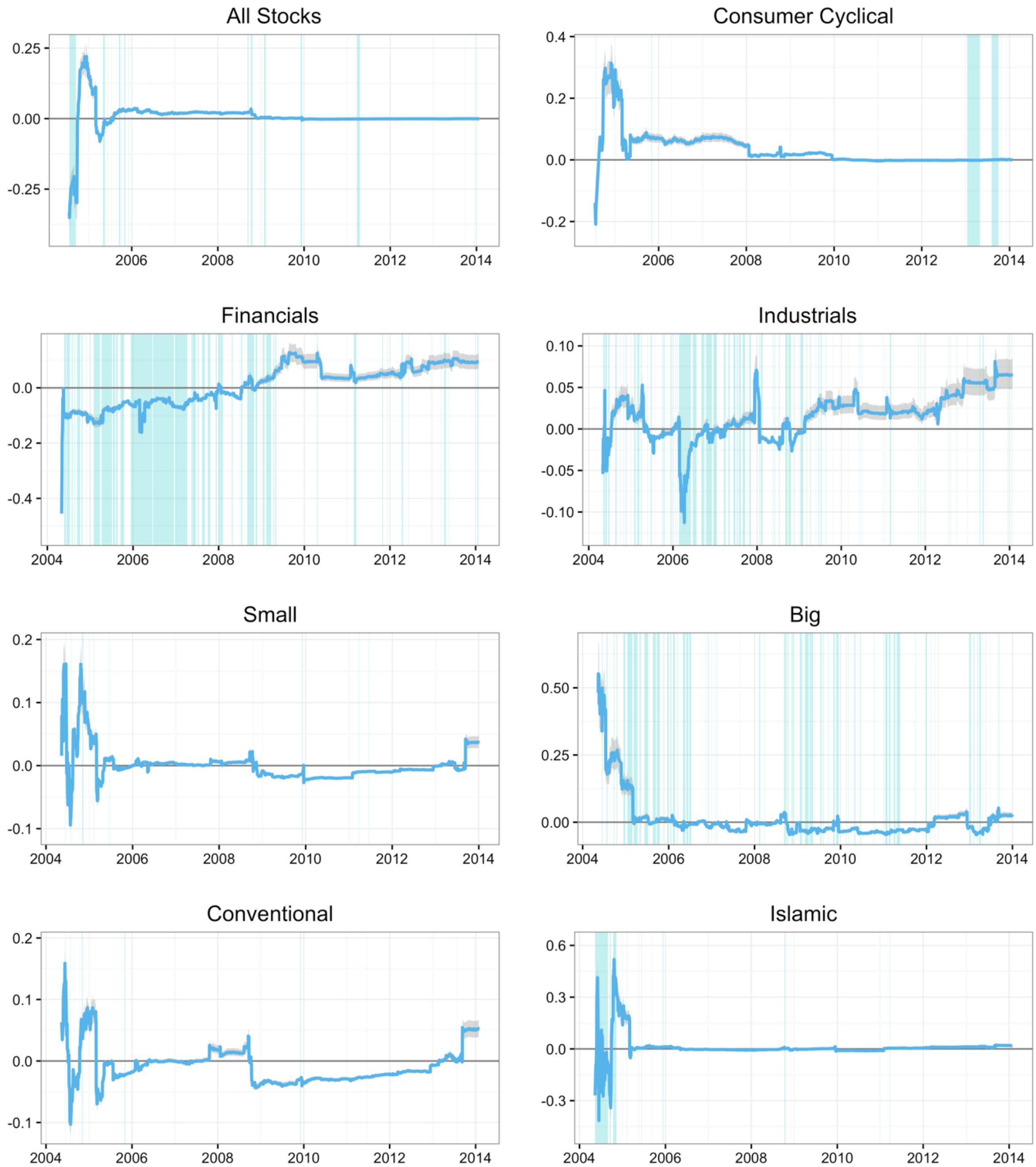
**Note:** The table reports the Pearson correlation coefficients of the time varying herding estimates ($\alpha_{2,t}$) with Brent oil returns and the oil market speculative ratio. The time varying herding coefficients ($\alpha_{2,t}$) are obtained from the MS-TVP herding model described in Equations (4)-(5). The speculative ratio is the daily open interest over the trading volume in the Brent oil futures market. The t-statistic for the significance of the correlation coefficients is given in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

**Figure 1. Estimates of the Time Varying Herding Coefficients for Saudi Arabia**



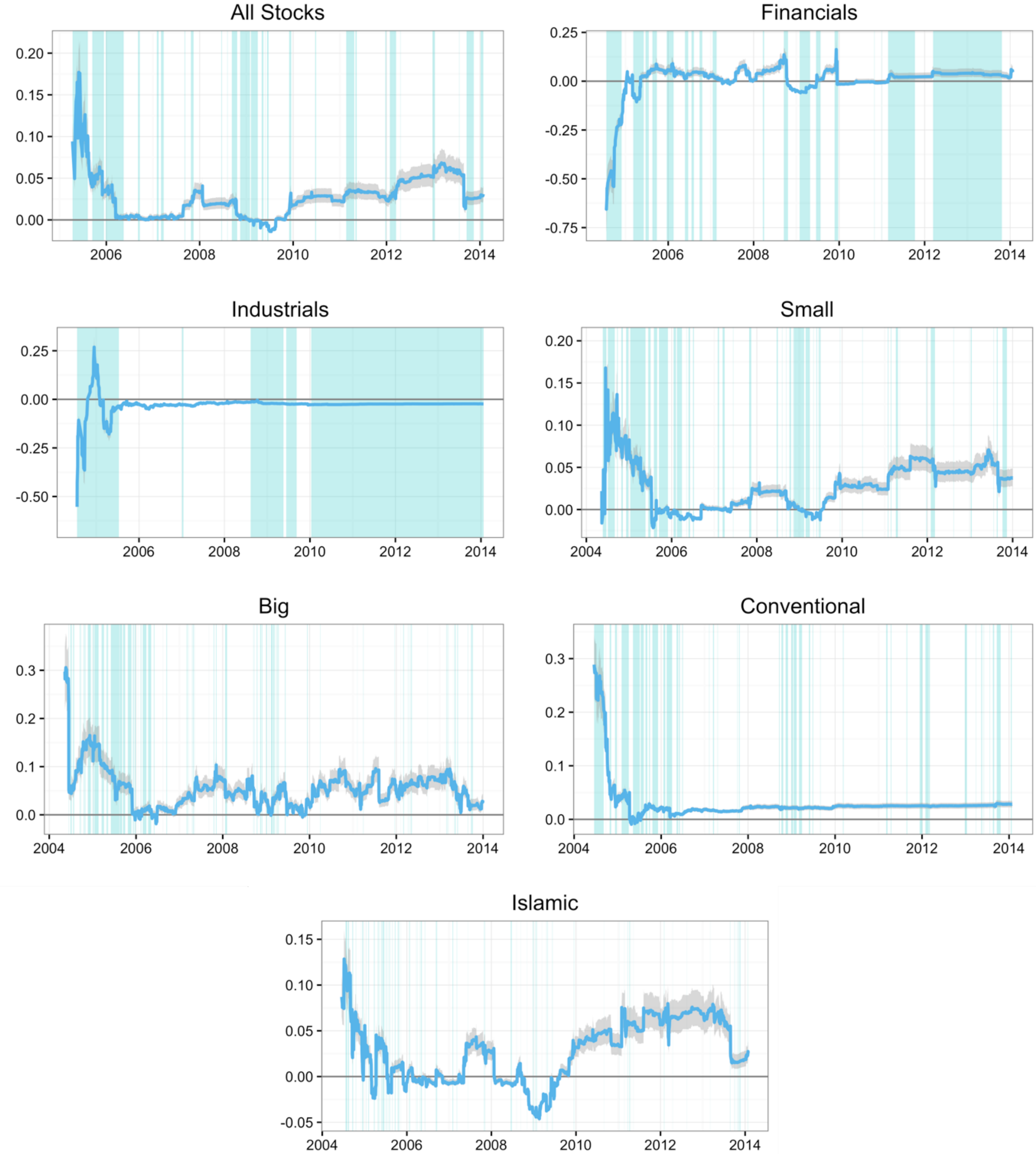

**Note**: The figure plots the estimates of the time varying herding coefficient $\alpha_{2,t}$ from the MS-TVP herding model defined in Equations (4)-(5). The gray shaded bands represent the 95% confidence intervals computed using the estimate of the variance of $\alpha_{2,t}$ in Table 5. The estimates for $t = 1, ,2 \ldots ,20$ are excluded since the Kalman filter requires a burn-in period for the parameters to converge. The vertical shades (in light green) mark the high volatility regime (Regime 2) determined based on the maximum of the smoothed regime probabilities.

**Figure 2. Estimates of the Time Varying Herding Coefficients for Abu Dhabi**



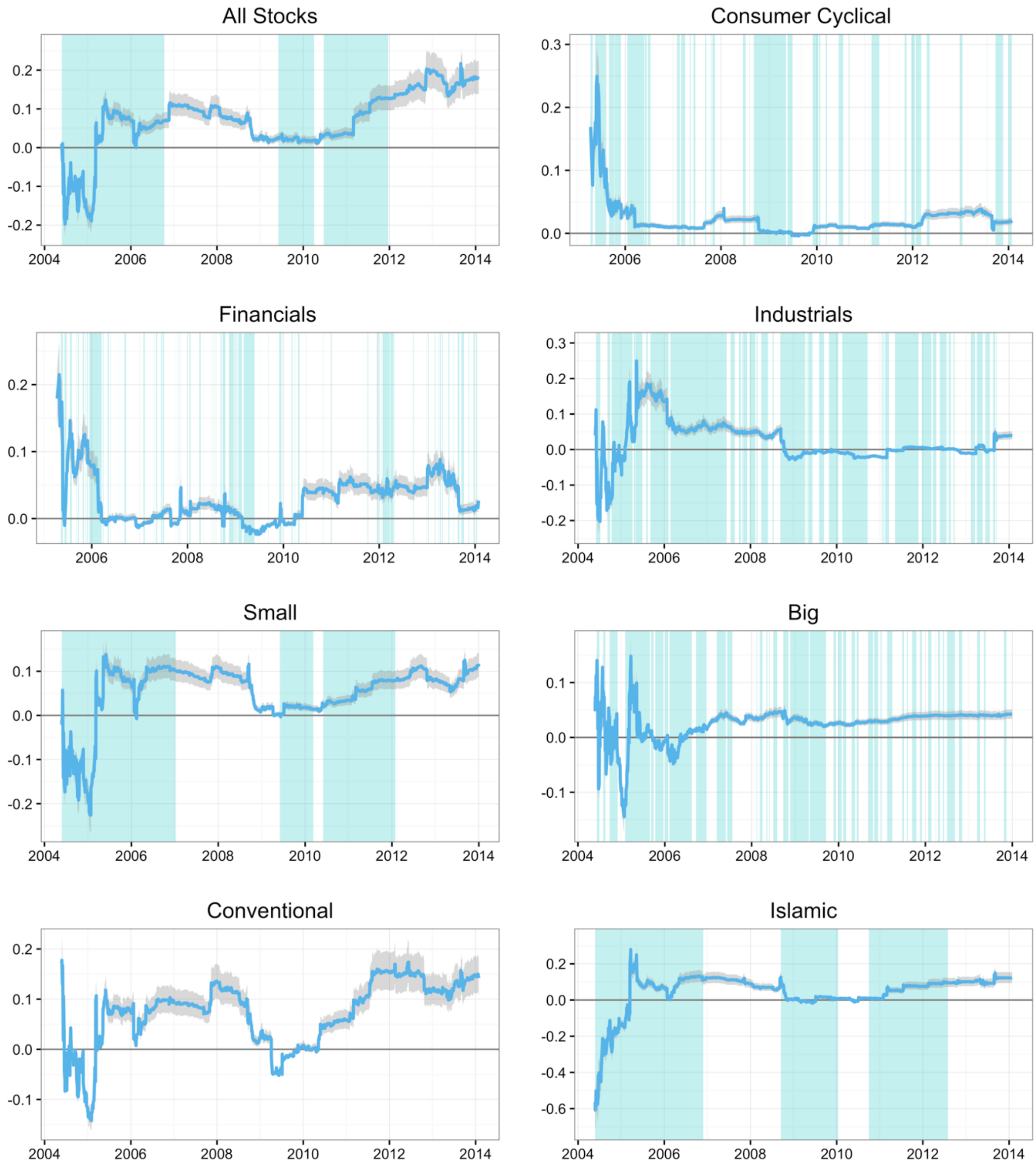

**Note**: See note to Figure 1

**Figure 3. Estimates of the Time Varying Herding Coefficients for Dubai**



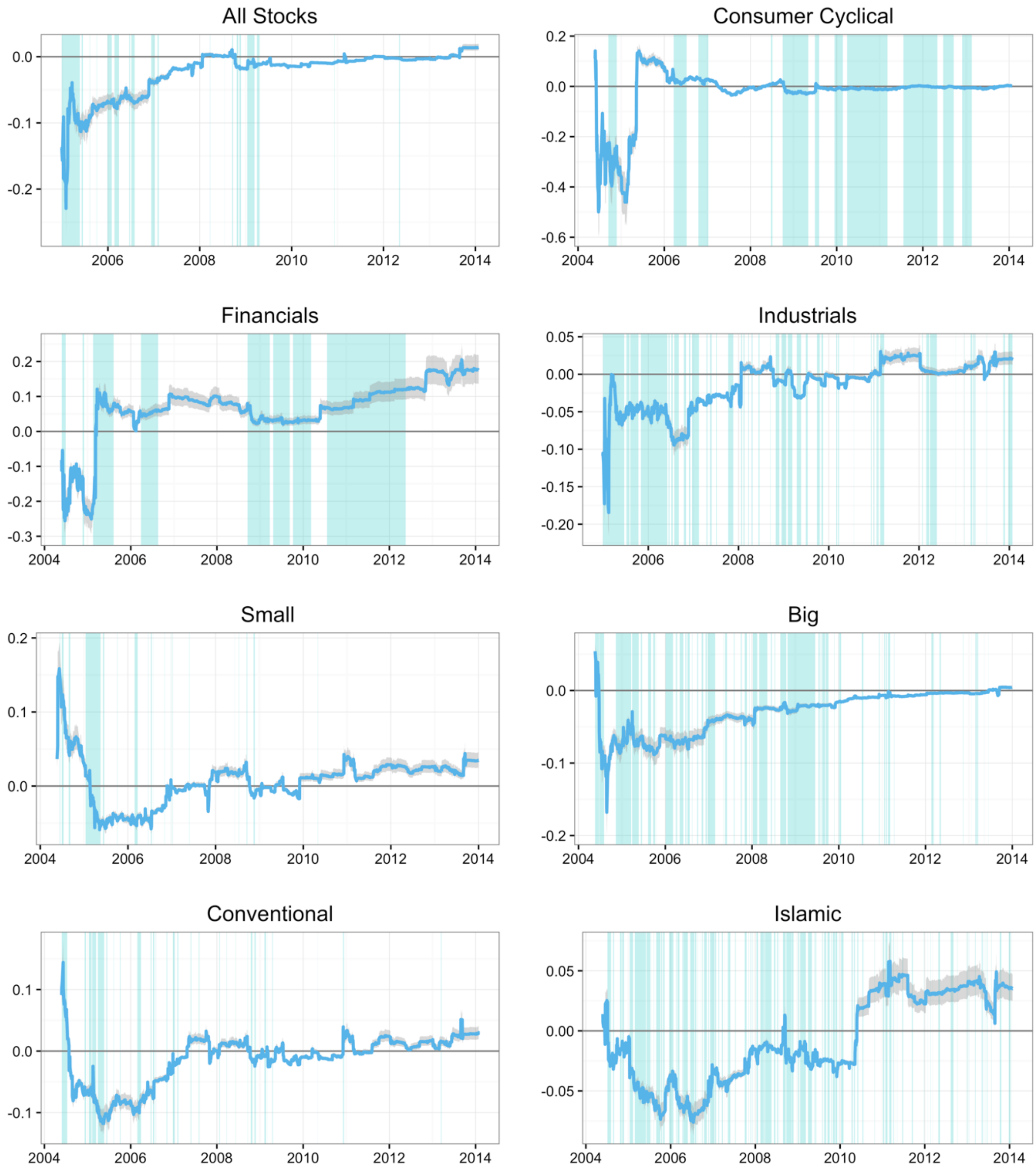

**Note**: See note to Figure 1

**Figure 4. Estimates of the Time Varying Herding Coefficients for Kuwait**




**Note**: See note to Figure 1

**Figure 5. Estimates of the Time Varying Herding Coefficients for Qatar**




**Note**: See note to Figure 1