The Effect of Gold Market Speculation on REIT Returns in South Africa: A Behavioral Perspective

Kola Akinsomi
School of Construction Economics and Management,
University of Witwatersrand, Johannesburg, 2000, South Africa
E-mail address: Kola.Akinsomi@wits.ac.za

Mehmet Balcilar
Department of Economics, Eastern Mediterranean University,
Famagusta, Turkish Republic of Northern Cyprus, via Mersin 10, Turkey;
Department of Economics, University of Pretoria,
Pretoria, 0002, South Africa;
IPAG Business School, Paris, France
E-mail address: mehmet@mbalcilar.net

Rıza Demirer
Department of Economics & Finance
Southern Illinois University Edwardsville
Edwardsville, IL 62026-1102, USA
E-mail address: rdemire@siue.edu

Rangan Gupta
Department of Economics,
University of Pretoria,
Pretoria, 0002, South Africa;
IPAG Business School, Paris, France
E-mail address: rangan.gupta@up.ac.za

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Abstract

This study provides novel insight to the evolution of herd behavior during crisis periods by relating the time-variation in investor herding to speculation in gold, an asset traditionally considered a safe haven during periods of market crisis. We find that higher level of speculation in gold significantly contributes to herding in the emerging South African real estate investment trust (REIT) market, particularly during the mid-2008 to 2011 period, matching the duration and aftermath of the global financial crisis. The evidence of herding in this market is in contrast to the static and two-regime model specifications that fail to detect herding, underscoring the significance of econometric specifications that directly track the time-variation in herd behavior. Our findings suggest that speculative activities in the gold market contain valuable information regarding market fundamentals that drive investor behavior in emerging markets and that regulators should monitor indicators of speculative activities in gold in order to implement circuit breakers in their markets that may help mitigate the negative effects of herd behavior.

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1. Introduction

Recent market crises and volatility spillovers across global financial markets have triggered renewed interest in investor behavior, particularly during periods of market stress, and how it relates to stock market movements. Consequently, a number of papers have recently been published focusing on herd behavior among investors, with a wide range of applications in different contexts. While most of these studies document evidence of investor herding particularly in emerging stock markets and more prevalently during periods of market stress (e.g. Balcilar *et al*., 2013; Babalos *et al*., 2013; Yao *et al*., 2014; Balcilar and Demirer, 2015), a natural research question is whether certain global proxies of market stress can explain the evolution of herding or anti-herding in stock markets. If one can identify such global proxies of market stress that significantly influence investor behavior, particularly in emerging markets, then regulators in those countries can focus on those stress proxies in order to develop safety nets and circuit breakers that may help to prevent the destabilizing effects of investor herding as herd behavior might contribute to market volatility and pricing inefficiencies (e.g. Bikhchandani *et al*., 2001; Blasco *et al*, 2012).

This study provides novel insight to the evolution of herd behavior during crisis periods by relating the time-variation in investor herding to speculation in the gold market, an asset traditionally considered a safe haven during periods of market crisis (e.g. Baur and Lucey, 2010). Using firm-level data from South African Real Estate Investment Trusts (REITs), a major emerging market in BRICS, we examine how speculative activities in the gold market relate to the time-variation in investors' herding or anti-herding patterns. The decision to look at herding behavior in South African REITs is motivated by certain statistical facts: First, according to SA REIT Association (2015a), South Africa's listed properties asset class has outperformed cash, equities and bonds for more than 10 years. Second, SA REITs have also outperformed developed economies' REITs over the last 10 years as the listed property sector in South Africa has grown quite significantly and continues to grow (SA REIT Association, 2015a).[1] Therefore, one can argue that the fast growth and the attractive yields offered in this market segment have triggered interest among investors domestically and otherwise, potentially contributing to the presence of herding through correlated trades. Recognizing that this question can be answered empirically at best, the REITs market in this country provides an interesting avenue to examine herd behavior.

Relating investor behavior in South Africa to speculation in the gold market is primarily motivated by the role of gold as a traditional safe haven that investors flock to during periods of market crisis. It can be argued that gold market dynamics, particularly during market crisis periods, are closely related to global expectations of economic fundamentals. To that end, the speculative ratio, a measure of speculative activity recently suggested by Chan *et al*. (2015), provides an interesting opening in that it allows us to examine whether the time variation in the level of speculation in this safe haven asset relates to investor herding in a major emerging stock market that has experienced some of the worst side effects of turbulence in global financial markets. A second motivation to relate gold speculation to herding in the South African REITs is due to the importance of the gold mining industry in this country that has been the driving force behind its economic growth and participation in the global economy (Mining Production and Sale Report, Statistics South Africa, 2015). It can be argued that, speculative activities in the gold market as a proxy of future expected prices, drives currency and stock market dynamics in South Africa.

In addition to its contribution to the herding literature, this study also contributes to the strand of the literature that deals with the relationship between commodities and stock markets as a number of papers have documented that commodities like gold and oil can help forecast real exchange rates in major commodity

[1] The process to establish SA REIT began in August 2006 and the process came to completion roughly three years later when the National Treasury released the 'white paper' on REITs in October 2009 (SA REIT Association, 2013). Amendments made to the Taxation Legislation (Taxation Legislation Amendment Bill) in 2013 cleared the way for REITs in South Africa and together with the JSE releasing the amended Sec 13 of their listing requirements, REITs were enabled to be listed as of 1 May 2013 (SA REIT Association, 2013). The SA REIT Association was thus launched on the 23rd of May 2013. As of June 2015 S&P Global Index included 13 South African REITs totaling a US$21.45 billion market capitalization invested into the portfolio of global REITs ranking South Africa 9th out of 23 countries represented in this Index with a market capitalization of US$20.094 million (Akinsomi et al., 2016). South Africa has two types of REITs; company REITs and Trust REITs (SA REIT Association, 2015 b).

exporters (e.g., Apergis, 2014). To that end, relating speculation in the market for gold to investor behavior in this major emerging stock market can enlarge our understanding of how commodity market dynamics relate to stock market dynamics in major exporting nations. Finally, a third contribution of this study is from an econometric perspective in that we propose a Markov switching time-varying parameter (MS-TVP) herding model that not only takes into account different market states during which herding or anti-herding may be present, but also directly relates the speculative ratio in the gold market to time-variation in the estimated herding coefficients. By doing so, this study contributes both to the herding literature and to the literature on commodity-stock market nexus.

We find that the benchmark herding models that are based on a static as well as a two-regime Markov switching (MS) specification fail to detect herding in this stock market. On the other hand, the MS-TVP specification which tracks the time-variation in the herding coefficient clearly identifies periods of herding and anti-herding where herding is largely concentrated on the period that corresponds to the duration and the aftermath of the global financial crisis. Interestingly, the two-regime MS model that tests for the presence of herding during the low and high volatility market states fails to detect herding even during the high volatility state, underscoring the significance of econometric specifications that directly track the time-variation in herding.

Examining the time-variation in speculative activities in the gold market, we observe that higher level of speculation in gold significantly contributes to herding in this emerging market. The significance of gold speculation is robust to alternative model specifications and suggests that speculation in this safe haven potentially contains significant information that relates to investor behavior in stock markets. Our analysis of dynamic correlations between the level of gold speculation and herding further supports the estimation results from the MS-TVP model, indicated by a negative correlation between the estimated herding coefficients and gold speculation, particularly during the mid-2008 to 2011 period, exactly matching the duration and aftermath of the global financial crisis. Overall, our findings suggest that speculative activities in the gold market contain valuable information regarding market fundamentals that drive investor behavior in emerging markets. A natural policy implication, therefore, is to monitor indicators of hedging and speculative activities in the gold market in order to implement circuit breakers that may help prevent market crashes in emerging markets that are prone to global shocks.

The rest of this paper is organized as follows. Section 2 briefly summarizes the literature on herding tests in stock markets and the gold- stock market relationship in the South African context. Section 3 presents the data and methodology. Section 4 provides the empirical findings and Section 5 concludes the paper.

2. Literature Review

As mentioned earlier, the literature on investor herding has experienced a surge in published papers, particularly following the 2007/2008 global financial crisis. Some of the pioneering works in this field include Christie and Huang (1995) and Chang *et al*. (2000) who propose a return dispersion based methodology to detect the presence of herding.[2] These herding tests that focus on the cross-sectional behavior of firm returns within portfolios consisting firms of similar characteristics have been applied to numerous advanced and emerging stock markets and in different variations of model specifications. Some of the well-cited applications of these tests include Demirer and Kutan (2006), Tan *et al*. (2008), Yao *et al*. (2014), and Demirer *et al*. (2015) on Chinese stocks and industries; Chiang and Zheng (2010) on a collection of advanced and emerging stock markets; Economou *et al*. (2011) on southern European stock markets; Balcilar *et al*. (2013, 2014) on the emerging and frontier Gulf Arab stock markets; Philippas *et al*. (2013) on real estate investment trusts; Balcilar and Demirer (2015) on the Turkish stock market; among others.

Recognizing the weakness of the benchmark herding models in Christie and Huang (1995) and Chang *et al*. (2000) that assume constant parameters and thus fail to account for the dynamic market states during which herding may or may not be present, recent works including Balcilar *et al*. (2013, 2014) and Balcilar and Demirer (2015) have proposed dynamic specifications that are based Markov switching. The evidence from

[2] Demirer *et al*. (2010) provide a review of the different testing methodologies based on return dispersion.

these studies imply a link between crisis periods and investor herding, confirming earlier arguments that herding would be more prevalent during periods of market stress (e.g. Christie and Huang, 1995; Bikhchandani and Sharma, 2001). However, none of these studies have extended the dynamic herding models to a time-varying parameter (TVP) specification that allows us to trace the evolution of herding or anti-herding over time. To that end, an econometric contribution of this study is to extend the literature to an MS-TVP specification and use this specification to relate the time-variation in herding to speculative activities in gold, that is long considered a safe haven during periods of market crisis.

The importance of mining, and gold particularly, in South Africa and its influence on the economy has been historically immense (Fedderke and Simkins, 2009; Gupta and Hartley, 2013). South Africa was the largest producer of gold globally until 2006 and gold mining in this country has been the driving force behind its economic growth and participation in the global economy (Fedderke and Pirouz, 2009; Gupta and Hartley, 2013). Although South Africa has now slipped to sixth in terms of gold production in the world, gold continues to remain one of the most important mining industries domestically, contributing to 1.7 percent of GDP and 12.5 percent of mineral sales (Mining Production and Sale Report, Statistics South Africa, 2015).[3] Gold is globally considered as a safe haven asset and subject to tremendous volume of trading activity, of which a significant proportion is linked to speculation. Therefore, given the importance of gold as a traditional safe haven, speculation in this asset, particularly during distressed market periods; and South Africa's contribution to its production, speculative activities in this asset can be expected to influence investor behavior in a BRICS economy like South Africa via multiple channels (Chinzara, 2011; de Bruyn et al., 2015).

3. Data and methodology

3.1 Data

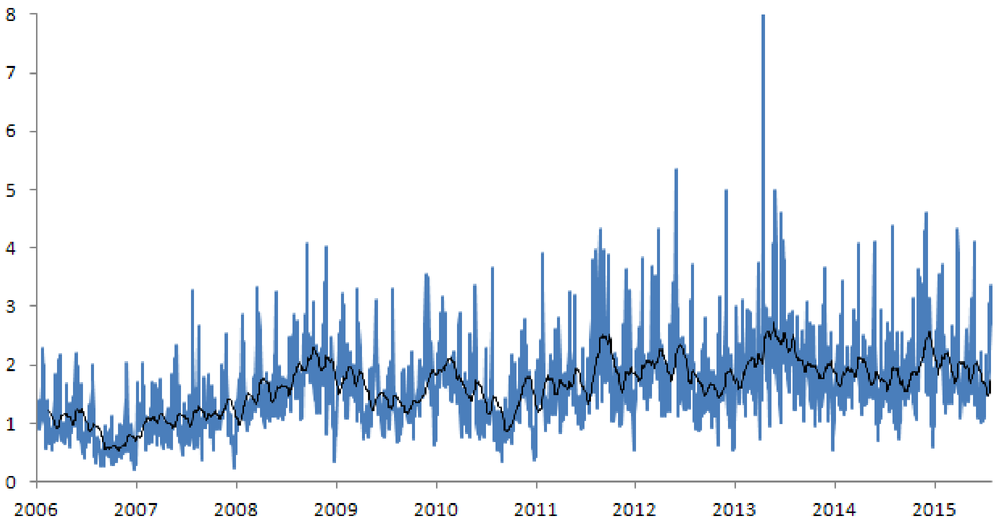
Following the suggestion in the herding literature that investor herding would be more likely to present itself within sufficiently homogeneous groups of market participants (e.g. Christie and Huang, 1995; and

[3] Coal currently leads the pack, having contributed 27 percent of total mineral sales in 2014.

Bikhchandani and Sharma, 2001), we focus on securities that are classified as real estate investment trusts. As mentioned earlier, the choice of REITs is largely motivated by not only the fact that South Africa's properties asset class has outperformed cash, equities and bonds, but is also based on the observation by Fedderke and Pirouz (2009) that the output of the mining sector has contributed to sharp increases in real wages, with potential effects on the growth of the real estate sector in South Africa. Therefore, for our empirical analysis, we use daily data comprising of 25 REITs on the Johannesburg Stock Exchange over the period 1 January 2005 to 31 July 2015, giving us a total of 2,640 observations. The data is sourced from INET BFA McGregor database.

As mentioned earlier, one of the contributions of this study is to relate, via the MS-TVP specification, the time-variation in herding to speculative activities in the gold market. For this purpose, we obtain daily data on gold futures from Commodity Systems Inc. and calculate the speculative ratio defined as the trading volume divided by open interest, following Chan *et al*. (2015). Figure 1 plots the daily speculative ratio normalized to one at the beginning of the sample period for illustrative purposes. We observe notable spikes in the level of speculative activity in the gold market, one of which is for the duration and the aftermath of the global crisis in late 2008.

Figure 1. Gold speculative ratio.



Note: Figure plots the daily speculative ratio for gold futures defined as the ratio of trading volume to open interest over the sample period 1/4/2006-7/27/2015. The values are rebased at 1 at the beginning of the sample period for illustrative purposes. The black solid line indicates the 30-day moving average.

Examining the 30-day moving average indicated by the solid black line in Figure 1, we also observe several other outbreaks of speculative activity during periods that correspond to Eurozone crisis, particularly that involve bailout discussions for Greece during early 2010 when the IMF and EU agreed to provide Greece 110 billion euro in loans, late 2011 when the Greek prime minister proposed a referendum on bailout and mid-2013 when the Greek parliament announced its approval of austerity measures. Another notable outbreak in gold speculation is also observed during late-2014 and early-2015 when the ECB announced a 1.1 trillion euro quantitative easing program. To that end, it is quite interesting that the time-variation in the speculative ratio for this safe haven mirrors some of the notable market stress points in time and further supports the choice of this variable as a determinant in our MS-TVP herding model.

3.2 Testing methodology

The methodology to detect herding follows a number of studies including Chang *et al*. (2000), Gleason *et al*. (2004), Tan *et al*. (2008), Demirer *et al*. (2010, 2014), Chiang and Zheng (2010), Economou *et al*. (2011), Balcilar *et al*. (2013, 2014), Babalos *et al*. (2013, 2015) and Balcilar and Demirer (2015), among others. Originally, developed by Christie and Huang (1995) and later improved by Chang *et al*. (2000), the test employs return data across securities of similar characteristics. Unlike other herding tests that require transaction or holding data which is often available at quarterly basis, the use of daily return data in this particular methodology allows us to trace the time-variation in herding to gold market dynamics and is preferable in the particular context of this study.

The benchmark model is developed from the CAPM specification of returns and uses the deviations from the CAPM to make inferences on the presence of herding. The test focuses on the cross-sectional absolute deviation of returns (CSAD) expressed as

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

where N is the number of REITs in the portfolio, $R_{i,t}$ is the observed return on REIT i for day t and $R_{m,t}$ is the return on the market portfolio for day t. Following the CAPM specification, the expected value of the return dispersion measure described by CSAD in Equation 1 can be expressed as $E(CSAD_t) = \frac{1}{N}\sum_{i=1}^{N} | \beta_i - \beta_m | E(R_m - R_z)$ where R_z is the return on the zero-beta portfolio and β_i is the systematic risk exposure of REIT i with respect to the market factor. One can then show that expected CSAD should, in theory, have a non-negative relation with the expect market return (implied by non-negative first derivative with respect to expected market return) while the second derivative with respect to the market return is zero. This implies that greater cross-sectional dispersion in asset returns should, in theory, be expected for larger market movements and the relationship between market return and cross-sectional return dispersion should be linear.

On the other hand, according to the CAPM specification, the second derivative of the CSAD term with respect to market return is expected to be zero, indicating a linear relationship between asset betas and expected returns. As a result, using the CAPM specification of returns as a basis, Chang *et al*. (2000) propose the following quadratic benchmark model

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

where a significant and negative estimate for α_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 (α_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.

In this study, we extend the original herding model of Chang *et al*. (2000) in Equation (3) in four ways. First, following Chiang and Zheng (2010), we allow asymmetric investor herding behavior in up and down markets. The asymmetric herding behavior is introduced by including $R_{m,t}$ as an additional regressor in Equation (3) as follows

$$CSAD_t = \alpha_0 + \alpha_1 |R_{m,t}| + \alpha_2 R_{m,t}^2 + \alpha_3 R_{m,t} + \varepsilon_t \quad \textbf{(4)}$$

As Duffee (2001) points out, the impact of $R_{m,t}$ on $CSAD_t$ is given by $(\alpha_1 + \alpha_3)$ in up markets ($R_{m,t} > 0$), while the difference $(\alpha_1 - \alpha_3)$ captures the impact of the market return $R_{m,t}$ on $CSAD_t$ in down markets ($R_{m,t} < 0$). The degree of asymmetry between the $CSAD_t$ and $R_{m,t}$ is then measured by the ratio $(\alpha_1 + \alpha_3)/(\alpha_1 - \alpha_3)$.

The second improvement of the original model follows the evidence in the herding literature that herding is highly related to market regimes and is more prevalent during volatile market periods (e.g. Balcilar *et al*., 2013, 2014). Therefore, following Balcilar *et al*. (2013, 2014), we consider herding in a Markov switching (MS) specification with two regimes in which the regimes signify up and down markets. The MS extensions of the herding models in Equations (3) and (4) are specified as

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t}|R_{m,t}| + \alpha_{2,S_t}R_{m,t}^2 + \varepsilon_t \quad \textbf{(5)}$$

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t}|R_{m,t}| + \alpha_{2,S_t}R_{m,t}^2 + \alpha_{3,S_t}R_{m,t} + \varepsilon_t \quad \textbf{(6)}$$

where $S_t \in \{0,1\}$ is the latent regime variable following a two-state, first order Markov process that represents low and high volatility market states and ε_t has a heteroskedastic normal distribution, i.e., $\varepsilon_t \sim N\left(0, \sigma_{\varepsilon,S_t}^2\right)$.

Third, following the argument by Froot *et al*. (1992) of a possible link between speculative activities and investor herding and the evidence by Balcilar *et al*. (2013, 2014) that herding and market volatility are closely related, we conjecture that the intensity of herding measured by the coefficient α_2 in Equation (3) is likely to depend on the level of speculative activity as well as market volatility. Therefore, as a third extension, we allow the intensity of herding to depend on the speculative activity and market volatility.

Finally, considering the dynamic nature of herding that may be present during certain market conditions only and the weakness of the static specification of the benchmark model in Equation (3), we accommodate the time-variation in the level of herding by allowing the parameters of the herding model in Equations (3) and (4) to change over time with the use of a time-varying parameter (TVP) model. As a result, in order to accommodate both the time-variation and regime switching in our estimations as well as the effects of speculative activity and market volatility on the time-variation in herding, we propose a Markov switching time-varying parameter (MS-TVP) herding model specified as follows:

$$CSAD_t = \alpha_{0,t} + \alpha_{1,t}\left|R_{m,t}\right| + \alpha_{2,t}R_{m,t}^2 + \alpha_{3,t}R_{m,t} + \varepsilon_t \quad \textbf{(7a)}$$
$$\alpha_{2,t} = \alpha_{2,t-1} + \mu_{S_t} + \theta_{S_t}\sigma_t^2 + \gamma_{S_t}\xi_t + \nu_{2,t}, \quad \textbf{(7b)}$$
$$\alpha_{i,t} = \alpha_{i,t-1} + \nu_{i,t}, \quad i = 0,1,3 \quad \textbf{(7c)}$$
$$\varepsilon_t \sim N\left(0, \sigma_{\varepsilon,S_t}^2\right), \quad S_t \in \{0,1\} \quad \textbf{(7d)}$$
$$\nu_{i,t} \sim N(0, \sigma_{\nu_i}^2) \quad \textbf{(7e)}$$
$$\sigma_{\varepsilon,S_t}^2 = \sigma_{\varepsilon,0}^2(1 - S_t) + \sigma_{\varepsilon,1}^2 S_t, \quad \sigma_{\varepsilon,1}^2 > \sigma_{\varepsilon,0}^2 \quad \textbf{(7f)}$$
$$P[S_t = 1|S_{t-1} = 1] = p_{11}, \quad P[S_t = 2|S_{t-1} = 2] = p_{22} \quad \textbf{(7g)}$$

where N denotes the normal distribution, ξ_t is the speculative ratio variable defined as the ratio of daily trading volume to open interest, the conditional variance σ_t^2 in Equation (7b) is obtained as $\sigma_t^2 = p_{0,t|t-1}\sigma_0^2 + p_{1,t|t-1}\sigma_1^2$ where $p_{i,t|t-1}$ is the predictive probability for regime i, and $p_{ij} = P[S_t = i|S_{t-1} = j]$, $i,j = 0,1$, is the probability of being in regime i iat time t given that the market was in regime j at time $t-1$ with regimes i and j taking values in $\{0, 1\}$. Finally, the transition probabilities satisfy $\sum_{i=1}^{2} p_{ij} = 0$, $j = 0,1$. Note that the condition $\sigma_{\varepsilon,1}^2 > \sigma_{\varepsilon,0}^2$, which implies that the second regime (Regime 1) is the high volatility or hectic regime. The MS-TVP model is specified in a way that all parameters, including the herding coefficient ($\alpha_{2,t}$) 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.

Overall, the MS-TVP specification in Equation (7) presents several novelties: (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 modeled 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 becomes 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

Table 1 provides the summary statistics for daily cross-sectional return dispersions for REITs, market return and the speculative ratio for the gold market. We observe a positive mean return for the REITs market despite the inclusion of the global financial crisis period in our sample. The estimated kurtosis value that is higher than the normal distribution implies the presence of extreme movements in REIT returns in either direction, thus supporting the use of the t-distribution in the estimation process. The table also suggests that the CSAD, market return ($R_{m,t}$) and speculative ratio (ξ_t) are all serially correlated and display conditionally heteroskedastic behavior.

Panels B and C provide the Pearson correlation coefficient estimates for the full sample and the global financial crisis period, respectively. The correlation coefficient estimates in panels B and C do vary significantly, implying the significance of structural breaks or regime-switching. Particularly, the correlations of the CSAD term with the market return and the speculative ratio are twice as high in the high volatility global financial crisis period compared to the full sample period, while its correlation with the squared and absolute market returns are lower in the crisis period. Other correlation estimates also vary significantly during the global financial crisis period, motivating the use of a dynamic, regime-switching model that takes into account possible structural breaks in the herding behavior.

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

Table 1. Descriptive Statistics

	$CSAD_t$	$R_{m,t}$	ξ_t
***Panel A**: Descriptive statistics*			
Mean	1.4081%	0.0546%	34.1549%
S.D.	0.8402%	0.8238%	15.7263%
Min	0.1741%	-4.7102%	4.5620%
Max	6.9889%	4.7547%	176.0064%
Skewness	2.2425%	-0.2036%	1.2366%
Kurtosis	7.5338%	3.9718%	4.0451%
JB	8119.3980***	1685.1260***	2375.1830***
Q(1)	184.0088***	144.4259***	1191.7583***
Q(5)	903.3095***	172.4098***	3499.2025***
ARCH(1)	39.5378***	186.8012***	372.9592***
ARCH(5)	242.2659***	325.3565***	386.2697***

***Panel B:** Pearson correlation coefficient estimates for the full sample*

	$CSAD_t$	$R_{m,t}$	ξ_t	$R^2_{m,t}$	$\lvert R_{m,t}\rvert$
$CSAD_t$	1.0000				
$R_{m,t}$	-0.0477	1.0000			
ξ_t	0.0582	-0.0641	1.0000		
$R^2_{m,t}$	0.3168	-0.0292	0.1180	1.0000	
$\lvert R_{m,t}\rvert$	0.3334	-0.0111	0.1224	0.8939	1.0000

***Panel C:** Pearson correlation coefficient estimates for the subprime mortgage crises period (Dec 2007-Jun 2009)*

$CSAD_t$	1.0000				
$R_{m,t}$	0.0999	1.0000			
ξ_t	0.1218	-0.0511	1.0000		
$R^2_{m,t}$	0.1233	0.2090	0.1216	1.0000	
$\lvert R_{m,t}\rvert$	0.1282	0.1085	0.1816	0.9068	1.0000

Note: Panel A reports the descriptive statistics for cross sectional return dispersions for REITs ($CSAD_t$), market returns for REITs ($R_{m,t}$), and speculative ratio (ξ_t). Sample period covers 1/4/2006-7/27/2015 at daily frequency with 2530 observations for each series. $CSAD_t$ is the cross-sectional absolute deviation of returns as a measure of return dispersion. $R_{m,t}$ is the REITs market log return in percent. ξ_t is the speculative ratio defined as the trading volume divided by open interest in percent. In addition to the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Bera normality test (JB), the Ljung-Box first [*Q*(1)] and the fifth [*Q*(5)] autocorrelation tests, and the first [ARCH(1)] and the fifth [ARCH(4)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH). Panels B and C provide the Pearson correlation coefficient estimates for the full sample and for the subprime mortgage crises period of Dec. 2007-Jun 2009, respectively. The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

4.2 Evidence from benchmark models

Table 2 presents the estimation results for the benchmark model with and without the asymmetry term described in Equations 3 and 4, respectively. Panels A and B report the estimates for the static and two-state MS specifications for the benchmark model, respectively. We observe that, consistent with the CAPM specification, the linear term (α_1) is significant and positive in all model specifications, implying that REITs display greater cross-sectional dispersion in returns for larger market movements, which is due to the cross-sectional variation in the risk exposures of individual securities to the market factor.

Examining the herding coefficients, we observe that neither the static nor the two-state MS model is able to detect herding in this market, implied by insignificant (α_2) estimates. Interestingly, even the two-state MS specification that accounts for normal and hectic market regimes is not able to detect herding, further supporting the case for a time-varying parameter model to examine the dynamic nature of herding pattern in this market. Finally, we observe that the asymmetry term (α_3) is significant only during the post-crisis period, implying the presence of directional asymmetry in herd behavior during crisis periods.

4.3 Time-variation in herding and gold market speculation

As explained earlier, one of the novelties of the MS-TVP specification presented in Equation 7 is that it endogenously models the time-variation in herding by allowing the parameters of the model to stochastically evolve over time. Furthermore, this specification allows us to relate the time-variation in herding to market volatility and the level of speculation in the gold market via Equation 7b. Panel A of Figures 2 and 3 presents the estimated herding coefficients for the MS-TVP model with and without the asymmetry term, respectively. We observe that the estimated herding coefficients indeed display significant time variation with frequent switches from herding to anti-herding, implied by the negative and positive α_2 estimates, respectively. Notable herding periods are observed, particularly during high market volatility states indicated by the vertical shades in the plot. Interestingly, despite the failure of the static and the two-state MS specifications to detect herding (Table 2), we observe in Figures 2 and 3 (Panel A) that the market enters into a long-run herding pattern starting

Table 2. Estimates for the benchmark static and MS herding models.

Panel A: Benchmark static model with and without the asymmetry term (α_3)

	Full Sample	Pre-crises	Post-crises	Full Sample	Pre-crises	Post-crises
α_0	1.1663***	1.2689***	1.0763***	1.1674***	1.2695***	1.0780***
	(0.0282)	(0.0550)	(0.0311)	(0.0282)	(0.0549)	(0.0313)
α_1	0.3591***	0.5338***	0.1771*	0.3637***	0.5423***	0.1804*
	(0.0702)	(0.1233)	(0.0943)	(0.0700)	(0.1241)	(0.0951)
α_2	0.0475*	0.0045	0.0825*	0.0455	0.0000	0.0822*
	(0.0281)	(0.0452)	(0.0469)	(0.0281)	(0.0461)	(0.0471)
α_3				-0.0432*	-0.0389	-0.0568**
				(0.0232)	(0.0400)	(0.0254)
n	2530	944	1452	2530	944	1452
RSS	1583.5812	844.8635	479.4723	1580.3918	843.6704	476.8947
log L	-2997.2235	-1287.1090	-1255.8827	-2994.6731	-1286.4420	-1251.9692
AIC	2.372	2.733	1.734	2.370	2.734	1.730
Asym				0.7879	0.8661	0.5209

Panel B: Benchmark MS model with and without the asymmetry term (α_3)

	Full Sample	Pre-crises	Post-crises	Full Sample	Pre-crises	Post-crises
$\alpha_{0,0}$	0.9404***	0.9858***	0.8867***	0.9418***	0.9887***	0.8866***
	(0.0184)	(0.0355)	(0.0215)	(0.0186)	(0.0363)	(0.0214)
$\alpha_{0,1}$	2.0110***	2.2681***	1.6896***	2.0165***	2.2717***	1.6881***
	(0.0989)	(0.1868)	(0.1037)	(0.0995)	(0.1884)	(0.1035)
$\alpha_{1,0}$	0.3089***	0.4695***	0.2374***	0.3247***	0.4861***	0.2404***
	(0.0419)	(0.0760)	(0.0486)	(0.0436)	(0.0795)	(0.0483)
$\alpha_{1,1}$	0.4390***	0.6251**	0.3098*	0.4356***	0.6268**	0.3004
	(0.1646)	(0.2998)	(0.1849)	(0.1644)	(0.3011)	(0.1841)
$\alpha_{2,0}$	0.0185	-0.0190	0.0336*	0.0122	-0.0257	0.0340*
	(0.0164)	(0.0280)	(0.0201)	(0.0179)	(0.0308)	(0.0198)
$\alpha_{2,1}$	0.0109	-0.0557	0.0755	0.0067	-0.0627	0.0783
	(0.0492)	(0.0871)	(0.0501)	(0.0482)	(0.0859)	(0.0499)
$\alpha_{3,0}$				-0.0425***	-0.0327	-0.0431***
				(0.0133)	(0.0256)	(0.0140)
$\alpha_{3,1}$				0.0031	-0.0167	-0.0339
				(0.0512)	(0.0841)	(0.0678)
$\sigma_{\varepsilon,0}$	0.3767***	0.4427***	0.3162***	0.3791***	0.4478***	0.3133***
	(0.0106)	(0.0199)	(0.0116)	(0.0108)	(0.0204)	(0.0117)
$\sigma_{\varepsilon,1}$	1.0848***	1.2651***	0.7648***	1.0918***	1.2752***	0.7629***
	(0.0355)	(0.0647)	(0.0363)	(0.0360)	(0.0658)	(0.0361)
p_{00}	0.8994***	0.8833***	0.8621***	0.9047***	0.8914***	0.8586***
	(0.0146)	(0.0253)	(0.0200)	(0.0145)	(0.0255)	(0.0205)
p_{11}	0.6789***	0.6590***	0.4892***	0.6923***	0.6790***	0.4841***
	(0.0478)	(0.0804)	(0.0559)	(0.0471)	(0.0827)	(0.0563)
n	2530	944	1452	2530	944	1452
log L	-2470.0957	-1128.8526	-1070.9339	-2464.8206	-1127.9858	-1066.1746
AIC	1.9605	2.4128	1.4889	1.958	2.4152	1.4851
LR	1454.30	516.51	569.90	1459.70	516.91	571.59
	[<0.0000]	[<0.0000]	[<0.0000]	[<0.0000]	[<0.0000]	[<0.0000]
Asym						
Regime 0				0.7684	0.8738	0.6962
Regime 1				1.0143	0.9481	0.7974

Note: This table presents the estimates of static (Panel A) and the two-regime MS (Panel B) benchmark herding models given in Equation (5) (Model 1) and MS herding model with asymmetry term shown in Equation (6) (Model 2). The full sample period covers 1/4/2006 -7/27/2015, while the preand post-crises samples cover the periods 1/4/2006 -11/30/2007 and 7/1/2009 -11/30/2007, respectively. Herding coefficients are indicated in shaded rows; negative and significant values imply the presence of herding in the market. 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, log *L* is the log likelihood of the estimated model, AIC is the Akaike Information Criterion, and LR test is the linearity test. The LR test is nonstandard since there are unidentified parameters under the null and the Davies (1987) *p*-values are given in square brackets. Asym is the asymmetry measure defined as $(\alpha_{1,j} + \alpha_{3,j})/\ (\alpha_{1,j} - \alpha_{3,j})$ for regime *j* from Equation (6). The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

with the global financial crisis period in mid-2008 and lasts until mid-2013. This finding is rather striking in that even the dynamic, two-state MS specification fails to detect the presence of herding despite the fact that it differentiates normal and hectic market states when in fact herding is present. In contrast to the other studies where dynamic, regime-switching models are employed in herding tests (e.g. Balcilar *et al*., 2013, 2014), the failure of the MS model to detect herding in this particular case speaks to the strength of the TVP specification to capture herding and anti-herding patterns over time.

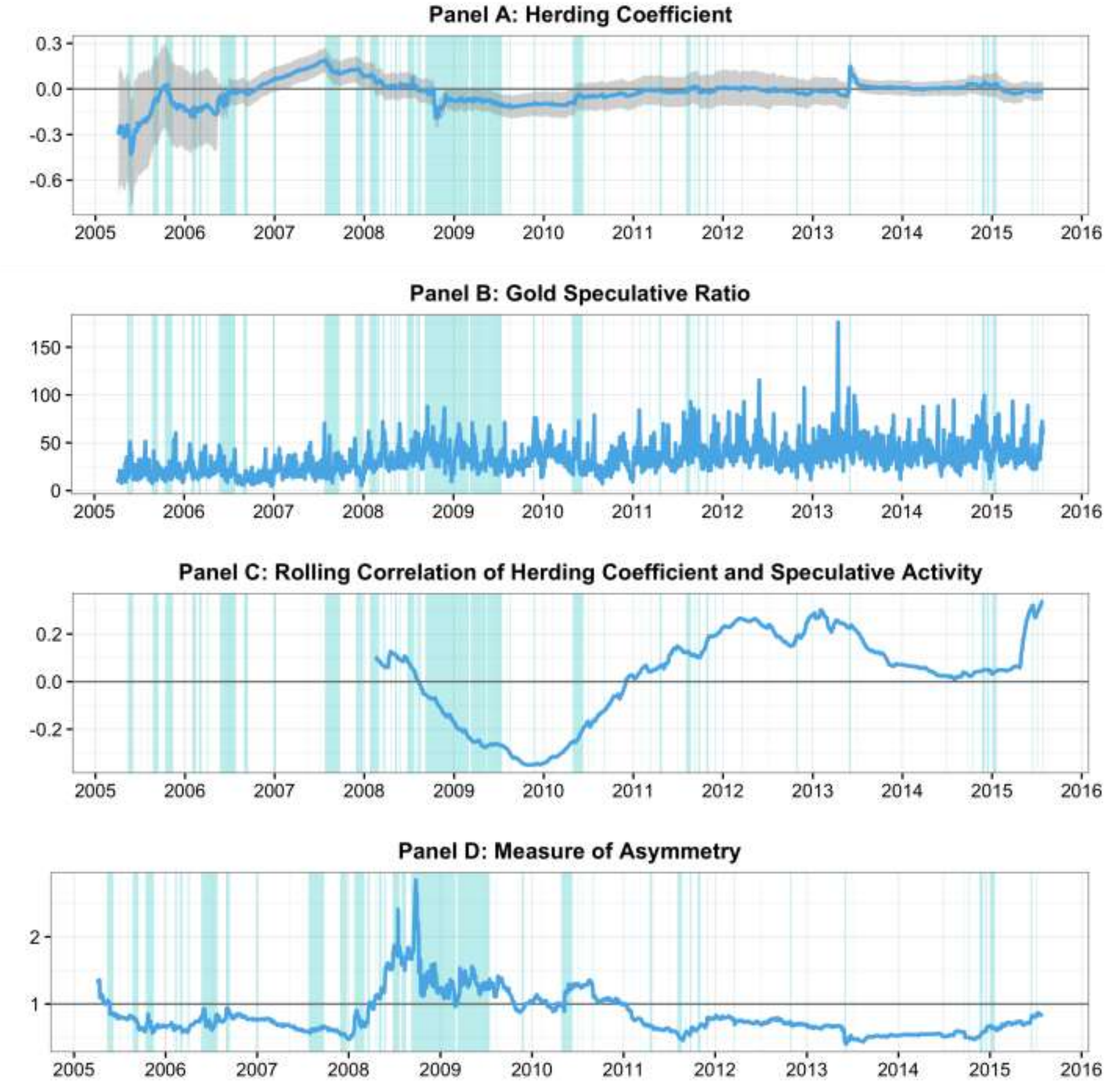
Table 3 presents the estimates for the variations of the MS-TVP model with and without the asymmetry term. Examining the estimated coefficients for the speculative ratio (γ_{S_t}) in Equation (7b), we observe that gold speculation has a significant effect on the herding coefficient only during the second regime, implied by the significant γ_1 estimates consistently across both specifications of the MS-TVP model. Comparing the estimated regime-specific volatility terms (σ_{ε,S_t}) in Table 3, the second regime is easily differentiated as the high volatility regime where the estimated volatility ($\sigma_{\varepsilon,1}$) is almost three times as high in the second regime as in the first regime ($\sigma_{\varepsilon,0}$). Thus, one can argue that speculative activities in the gold market relate to the presence of herding only during the high volatility market state and given the negative estimated γ_1 values in the second regime, we conclude that greater level of speculative activity in the gold market significantly contributes to herding in this emerging market. This observation becomes more meaningful with the positive estimates obtained for θ_{S_t} during the second regime, implying that herding and market volatility creates a vicious cycle in which market

Table 3. Estimates for the MS-TVP herding models.

Parameter	MS-TVP model with the asymmetry term	MS-TVP model without the asymmetry term
$\sigma_{\varepsilon,0}$	0.43210*** (0.01082)	0.43235*** (0.01057)
$\sigma_{\varepsilon,1}$	1.23193*** (0.05490)	1.24475*** (0.05370)
p_{00}	0.96412*** (0.00659)	0.96270*** (0.00653)
p_{00}	0.89414*** (0.02321)	0.88741*** (0.02334)
$\sigma_{v_0,0}$	1.1e-09 (0.01435)	2.8e-08 (0.01197)
$\sigma_{v_1,0}$	1.0e-09 (0.00213)	1.7e-09 (0.00183)
$\sigma_{v_2,0}$	1.8e-09 (0.00172)	1.9e-10 (0.00184)
$\sigma_{v_3,0}$	1.8e-09 (0.00387)	
$\sigma_{v_0,1}$	0.04790*** (0.00764)	0.05097*** (0.00764)
$\sigma_{v_1,1}$	0.00273 (0.00410)	4.1e-09 (0.00343)
$\sigma_{v_2,1}$	3.9e-09 (0.00278)	1.7e-09 (0.00303)
$\sigma_{v_3,1}$	0.00480* (0.00266)	
μ_0	-1.1e-03 (0.00312)	-5.9e-05 (0.00308)
μ_1	0.00591 (0.00892)	0.00361 (0.00723)
γ_0	0.01264 (0.01971)	0.00987 (0.01896)
γ_1	-1.1e-02** (0.00552)	-1.2e-02*** (0.00414)
θ_0	-3.0e-03 (0.00217)	-4.3e-03** (0.00195)
θ_1	0.02542* (0.01428)	0.02966** (0.01308)
p_0	0.7468	0.7512
p_1	0.2532	0.2488
d_0	27.8682	26.8113
d_1	9.4466	8.8817
n_0	1889.50	1900.44
n_1	640.50	629.56
log L	-2423.970	-2415.617
AIC	1.930	1.922

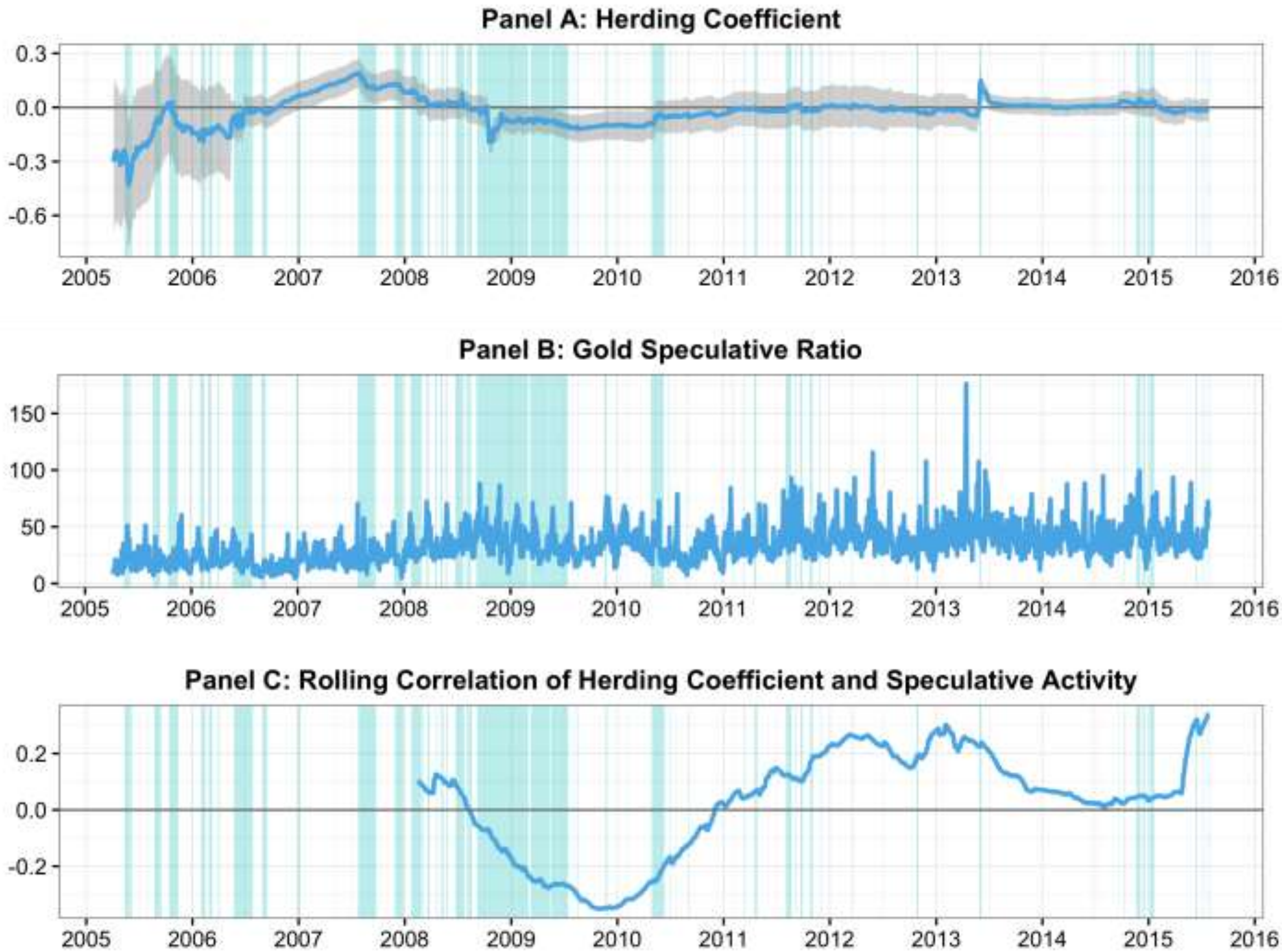
Note: The table reports the estimates for the MS-TVP herding models shown in Equation (7) for the period 1/4/2006-7/27/2015. The model descriptions are given in Table 1. $\sigma_{v_i,j}$, $i = 0,1,2,3$, $j = 0,1$, is the standard deviation of the error term ($v_{i,t}$) in Equation (7). $\sigma_{e,i}$, $i = 0,1$, is the regime-specific volatility estimate, p_{ij}, $i,j = 0,1$, is the transition probability from regime i in period $t-1$ to regime j in period t, p_i, $i = 0,1$, is the stationary (ergodic) probability of regime i, d_i, $i = 0,1$, is the duration of regime i, and n_i, $i = 0,1$, is the number of observations falling in regime i. 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. AIC denotes the Akaike Information Criterion. The numbers in parentheses are the standard errors.

Figure 2. Time-varying estimates from the MS-TVP model with asymmetry.



Note: The figure plots the estimates of the time varying herding coefficient $\alpha_{2,t}$ from the MS-TVP herding models defined in Equation (7). The gray shaded bands represent the 95% confidence intervals computed using the estimate of the variance of $\alpha_{2,t}$ defined in Equation (7b) which is obtained from the Kalman filter equations. The estimates for the first 60 periods 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 1) determined based on the maximum of the smoothed regime probabilities.

Figure 3. Time-varying estimates from the MS-TVP model without asymmetry.



Note: The figure plots the estimates of the time varying herding coefficient $\alpha_{2,t}$ from the MS-TVP herding models defined in Equation (7). The gray shaded bands represent the 95% confidence intervals computed using the estimate of the variance of $\alpha_{2,t}$ defined in Equation (7b) which is obtained from the Kalman filter equations. The estimates for the first 60 periods 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 1) determined based on the maximum of the smoothed regime probabilities.

volatility contributes to the formation of herding and herding drives up market volatility. Panel B of Figures 2 and 3 put this finding into perspective with periods characterized by statistically significant herding following a rising trend in speculative activity from the mid-2006 to end of 2008.

The contribution of gold speculation to investor herding is further supported by the analysis of rolling correlations between the estimated herding coefficients and the speculative ratio presented in Panel C of Figures 2 and 3. We observe that the correlations turn significantly to negative starting with mid-2008 when the global financial crisis broke out. Interestingly, this period is also associated with a notable outbreak in the estimated asymmetry measures (Panel D of Figure 2), consistent with the prevalence of herd behavior particularly during periods of large market losses, rather than bull market periods.

Chan *et al*. (2015) argue that the speculative ratio reflects the balance of hedging and speculative tendencies in the underlying commodity, implied by the level of trading volume relative to the open interest. It is therefore possible that increased speculative activity in the gold market, implied by higher speculative ratios particularly for the duration and aftermath of the global financial crisis period as shown in Figure 1, reflects increased uncertainty regarding global market conditions which also significantly contributes to herd behavior in the emerging South African REITs market that has been significantly affected by global market turbulence. To that end, one can argue that level of speculation in the gold market serves as a forward-looking global stress proxy implied by futures market transactions for this safe haven. This finding also suggests that policy makers should actively monitor this global market stress proxy as it may contribute to switches in investors' trading behavior where herding and market volatility forms a vicious cycle.

5. Conclusions

This study provides novel insight to the evolution of herd behavior during crisis periods by relating the time-variation in investor herding to speculation in the gold market, an asset traditionally considered a safe haven during periods of market crisis (e.g. Baur and Lucey, 2010). Using firm-level data from South Africa, a major emerging market in BRICS, we examine how speculative activities in the gold market relate to the time-variation in investors' herding or anti-herding patterns.

Utilizing a Markov switching time-varying parameter (MS-TVP) herding model, we show that the level of herding indeed exhibits a dynamic pattern in which the market switches between herding and anti-herding that cannot be detected by neither the static nor the two-state MS specifications. The failure of the MS model to capture the presence of herding despite its differentiation of market regimes underscores the significance of econometric specifications that directly track the time-variation in herding. The MS-TVP model indicates that the South African market entered into a long-run herding pattern starting with the global financial crisis period in mid-2008 and that the herding pattern lasted until mid-2013.

We also find that higher level of speculation in gold significantly contributes to herding in the South African REITs market, particularly during the mid-2008 to 2011 period, matching the duration and aftermath of the global financial crisis. The significant effect of gold speculation on herding is robust to alternative model specifications and suggests that speculation in this safe haven potentially contains significant information that drives investor behavior in this stock market. Interestingly, the period during which gold speculation is found to drive herding also corresponds to the market state in which volatility positively contributes to herding. This implies that herding and market volatility creates a vicious cycle in which market volatility contributes to the formation of herding and herding drives up market volatility, making it especially challenging for policy makers. We argue that regulators should monitor indicators of speculative activities in the gold market in order to implement circuit breakers that may help prevent market crashes in emerging markets that are prone to global shocks.

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