Impact of volatility and equity market uncertainty on herd behaviour: evidence from UK REITs

Omokolade Akinsomi
School of Construction Economics and Management, University of the Witwatersrand, Braamfontein, South Africa

Yener Coskun
Capital Markets Board of Turkey, Ankara, Turkey

Rangan Gupta
Department of Economics, University of Pretoria, Johannesburg, South Africa, and Chi Keung Marco Lau
Newcastle Business School, Northumbria University, Newcastle upon Tyne, UK

Abstract

Purpose – This paper aims to examine herding behaviour among investors and traders in UK-listed Real Estate Investment Trusts (REITs) within three market regimes (low, high and extreme volatility periods) from the period June 2004 to April 2016.

Design/methodology/approach – Observations of investors in 36 REITs that trade on the London Stock Exchange as at April 2016 were used to analyse herding behaviour among investors and traders of shares of UK REITs, using a Markov regime-switching model.

Findings – Although a static herding model rejects the existence of herding in REITs markets, estimates from the regime-switching model reveal substantial evidence of herding behaviour within the low volatility regime. Most interestingly, the authors observed a shift from anti-herding behaviour within the high volatility regime to herding behaviour within the low volatility regime, with this having been caused by the FTSE 100 Volatility Index (UK VIX).

Originality/value – The results have various implications for decisions regarding asset allocation, diversification and value management within UK REITs. Market participants and analysts may consider that collective movements and market sentiment/psychology are determinative factors of risk-return in UK REITs. In addition, general uncertainty in the equity market, proxied by the impact of the UK VIX, may also provide a signal for increasing herding-related risks among UK REITs.

Keywords Herd behaviour

Paper type Research paper

1. Introduction

The temper of the multitude is fickle.

Machiavelli

Decision-making in finance may inevitably involve discrepancies arising from reason such as information asymmetries or market-/person-specific investment psychology. The literature reveals that irrational features and behavioural aspects of the investment process, including non-financial assets and financial assets are among the reasons for anomalies and
boom-bust cycles. In this regard, despite well-established theoretical frameworks and empirical evidence on the efficient market hypothesis, financial markets involve widespread irrationalities. Global and market-specific uncertainties and volatilities have also exacerbated irrationalities in the leading and developing financial markets. It is not wrong to expect in light of past experiences that market and specific investment psychologies may go hand in hand, which may result in a market-wide roller-coaster effect during up- and down-market conditions in stock markets. As the signal of a crowd movement reflecting mass consensus, herd behaviour in direct and indirect property investments maybe also be analysed in the context of this irrational and inefficient roller-coaster effect.

Herding behaviour among investors and traders in property stocks has received increasing attention in the property literature. However, studies that have attempted to capture herding behaviour under different market regimes in Real Estate Investment Trusts (REITs) are still at an embryonic stage in the empirical literature. By using static and dynamic herding models, this study explores herding behaviour in UK-listed REITs over the period June 2004 to April 2016. Based on static modelling, we followed Chang et al. (2000) methodology, involving cross-sectional absolute standard deviations (CSAD) among individual firm returns, to define non-linear relations between equity return dispersions and market returns. In addition, we allowed the regime transition probabilities to be time varying, by using the time-varying transition probability Markov- switching model (TVTP-MS). Because the observation period involves twelve years before, during and after the Global Financial Crisis period, the evidence may imply that the UK REITs market inherently involves long run and persistent herding patterns. Due to the highly sophisticated nature of the London Stock Exchange (LSE), this behavioural phenomenon provides interesting evidence of herd behaviour from a developed-market perspective.

The UK REIT market was introduced in January 2007. Its introduction resulted in a number of previously listed UK property firms converting to REITs, as well as the initial public offerings of newly formed REITs being listed on the LSE. As at September 2017, the UK REIT market capitalization was valued at around £56bn[1]. The top five UK-listed REITs in market capitalization as at September 2017 included the Land Securities Group plc (£7.21bn), British Land (£6.14bn), SEGRO plc (£5.36bn), Hammerson plc (£4.26bn) and Intu properties plc (£3.12bn)[2]. The UK market is a significant global REIT market; for instance, according to the FTSE EPRA/NAREIT global REITs index as at 29 September 2017, UK REITs rank at number four in terms of weightage, with 5.34 per cent having a value of US $63.28bn, behind Japan (6.48 per cent, US$76.75bn), Australia (6.90 per cent, US$81.71bn) and the USA, which ranks number one, with a weight of 64.63 per cent and a value of US $765.51bn)[3].

The contribution of this study is threefold. Firstly, to the best of our knowledge, this paper is the first study to examine herding behaviour among investors in UK REITs. The intuition behind this investigation was to determine behavioural aspects in decision-making among investors in UK REITs, specifically to the interrelationships among uncertainty, volatility, and herding behaviour. Secondly, the study provides a study of the role of herding behaviour on the different regimes in the UK REIT market. Based on the selected analysis period, we provide comparative knowledge on herding in low, high and extreme market regimes. Threefold, using time-varying transition probabilities for herding behaviour, we also provide significant knowledge on the shifts between positive and negative herding behaviour during different volatility periods. In doing so, we used a new framework for analysing the destabilizing effects of herding in the UK REIT market. This analysis provides evidence from a developed country’s REIT market, such as that of the UK, which
may be found to be interesting as the prior literature reveals that herding is more likely to take place in emerging markets (Zhou and Anderson, 2013), and emerging markets have been found to exhibit higher herding levels compared with their developed market counterparts (Andronikidi and Kallinterakis, 2010). Overall, by focusing on UK REIT stocks during and after the Global Financial Crisis, the study opens a debate on whether UK REIT stocks show irrationalities from a herding perspective, as well as on whether the existing strategies of global portfolio managers and policy makers are compatible with a herding-based market structure.

The paper has four further sections. Section 2 reviews prior studies. Section 3 introduces the data and the testing methodology. The results based on the analysis of cross-sectional absolute standard deviations (CSAD) and time-varying transition probabilities are presented in Section 4. Finally, the Section 5 concludes the paper.

2. Literature review

As indicated in Keyne’s beauty-contest analogy, stock market investments are driven by the expectations of other investors, rather than by rational decisions based on analysis of the fundamentals of the asset. This “animal spirit” may be typically apparent during bubble (Kindleberger and Aliber, 2005; Akerlof and Shiller, 2009) or herding periods related to mass psychology and irrational price movements in stock markets. The main consensus among theoretical herding studies is that herding can be construed as being either a rational or irrational form of investment behaviour (Zhou and Anderson, 2013).

Herding is broadly perceived as an exuberant and irrational synchronized movement of asset prices, which is not justified by their fundamental values (Babalos et al., 2015). Bikhchandani and Sharma (2001) state that herding results from an obvious intent by investors to copy the behaviour of other investors and that imperfect information, concern for reputation and compensation structures are the potential reasons for rational herd behaviour in financial markets. Devenow and Welch (1996) postulate that despite the difficulty of defining herding, it could be defined as behaviour patterns that are correlated across individuals, and it is closely linked to such distinct phenomena as imperfect expectations, fickle changes without much new information, bubbles, fads, frenzies and sunspot equilibria.

Empirical studies on herding focus on either the behaviour of specific groups (i.e. mutual/pension fund managers, financial analysts) or on the overall market. For example, by examining the quarterly holdings of 155 mutual funds over the period 1975-1984, Grinblatt et al. (1995) found relatively weak evidence for mutual funds tending to buy and sell the same stocks at the same time. The studies selected – Chevalier and Ellison (1999), Graham (1999), Wermers (1999), Welch (2000), Hong et al. (2000), Gleason and Lee (2003) and Clement and Tse (2005) – also provided evidence of group-wide herding. On the other hand, by analysing 769 funds and the behaviour of pension managers, Lakonishok et al. (1992) found no evidence of market-wide herding but weak evidence of herding among smaller stocks and relatively little of either herding or positive-feedback trading among the largest stocks.

Analyses of herding under different market regimes provide interesting country-level outcomes. Hwang and Salmon (2004) analysed herding in the US and South Korean stock markets and found evidence of herding tendencies in market portfolios in both bull and bear markets. The authors further show that, contrary to common belief, the Asian crisis and particularly the Russian crisis, exhibited herding. Andronikidi and Kallinterakis (2010) found in the case of Israel that the presence of thin trading tends to conceal the actual magnitude of herding. Analysing Taiwanese open-end equity mutual fund herding behaviour over the period of 1996-2008, Hou et al. (2014) found evidence of both directional
and directionless herding, and the abolition of qualified foreign institutional investors has reduced directionless and sell-side herding but has had no effect on buy-side herding. Luo and Schinckus (2015) investigated herding behaviour in asymmetric (bearish versus bullish contexts) and extreme market conditions, using daily data from the Shanghai and Shenzhen stock exchange markets and found that a bullish context generates herding behaviour among investors of B-shares, while a bearish situation rather favours crowd movement among A-shares.

Herding in REIT stocks, the particular interest of this study, is a newly developing research area in the literature. As the first attempt to test herding in the REIT market, Zhou and Anderson (2013) investigated market-wide herding behaviour in the US equity REIT market by using the quantile regression method, and they found that herding is more likely to be present in the high quantiles of the REIT return dispersion. Authors further postulate that REIT investors tend to herd under turbulent market conditions, and that herding is more likely to occur and becomes stronger in declining markets, rather than in rising markets, implying asymmetry in herding behaviour. Moreover, the findings also show that during the Global Financial Crisis, REIT investors may not have started to herd until the market became extremely turbulent. By examining the existence of herding effects in the US REIT market during the period of January 2004 to December 2011, Philippas et al. (2013) found that a deterioration of investor sentiment and adverse macro-shocks to REIT funding conditions were significantly related to the emergence of herding behaviour, contrary to the common belief that the recent Financial Crisis did not seem to contribute to this phenomenon. The authors also documented asymmetric herding effects during the days of negative market returns. Babalos et al. (2015) explored herding under low, high and extreme market volatility regimes among US-listed REIT investors during January 2004 and June 2013, and using a regime-switching model, reveal substantial evidence of herding behaviour for the crash regime for almost all sectors, despite the static herding model’s rejection of the existence of herding. Moreover, the study suggests a shift from negative herding behaviour during low- and high-volatility regimes to positive herding behaviour under crash regimes for almost all REITs sectors. Using a Markov-switching time-varying parameter (MS-TVP) herding model for South African REITs, Akinsomi et al. (2017) found that higher levels of gold market speculation considerably contribute to herding behaviour in the South African REIT market and argue that herding and market volatility creates a vicious cycle in which market volatility contributes to the formation of herding, and herding in turn drives up market volatility, making it especially challenging for policymakers. By using Chang et al.’s. (2000) methodology over the period of July 2007 to May 2016 for Turkish REITs, Akinsomi et al. (2017b) found herding behaviour, the presence of directional asymmetry and linear relations between volatility and herding. The authors argue that herding is a persistent phenomenon and increases during periods of market stress in Borsa, Istanbul.

Maitland-Smith and Brooks (1999) applied and compared the properties of two regime-switching models for the value indices of commercial real estate in the USA and the UK, and found that the Markov-switching model is better able to capture the non-stationary features of the data than the threshold autoregressive model. By using a Markov-switching model, Krystalogianni and Tsolacos (2004) examined the structure of yields among broad asset classes (real estate, equities and government bonds) and its implications for portfolio allocation decisions and real estate investment. Liow and Zhu (2007) used a Markov-switching model to characterize real estate security markets’ risk-return and detected strong evidence of regimes in the six real estate security markets. In a different research field, Corradin and Fontana (2013) examined the house price dynamics of 13 European countries, using a Markov-switching error correction model. Lee et al. (2013) applied the bivariate
Markov-switching autoregressive model (MS-ARX) and the Markov-switching vector autoregression model (MSVAR) to identify the turning points of real estate cycles in Taiwan.

Despite a lack of studies on herding, the literature reveals interesting market characteristics applicable to UK REITs. For example, Barkham and Ward (1999) provide evidence regarding the relationship between the NAV discounts of UK property companies and their market capitalizations, based on various hypotheses. Analysing long memory in the returns and volatility of REITs markets in the USA, UK, Hong Kong, Australia and Japan, Assaf (2015) confirms that this phenomenon in volatility is real, and is not caused by shifts in variance across all markets. Lee (2013) found a high correlation between the various property types and regions in the UK and raises the question of how well diversified current institutional portfolios are in the UK. Galariotis et al. (2015) found that there have been herding spillover effects from the US to the UK during earlier financial crises and suggest that the drivers of herding behaviour are period- and country-specific.

Analysing UK REITs seems interesting for a number of reasons. The first point is that the UK real estate industry plays an important role in the national and international economy. As a reflection of this economic role, UK REITs are receiving increasing attention from investors. As indicated by Newell et al. (2016), UK REITs are an important property investment vehicle, being the fourth largest REIT market globally and having delivered strong risk-adjusted returns since the post-global financial crisis. Second, although our study is the first in the literature, the literature reveals that UK REITs show some anomalies and inefficiencies, implying that the industry may have further implicit irrationalities. For example, Jadevicius and Lee (2017) provide evidence that return anomalies exist among UK REITs, and investors can buy and sell them more effectively by recognizing the day-of-the-week effect. Morri and Baccarin (2016) investigated the NAV discount puzzle for REITs listed in France, The Netherlands and the United Kingdom between 2003 and 2014. The study suggests that in the UK and France, REITs with more debt are traded at higher discounts, and larger REITs trade at higher discounts in France and the UK, even though the relationship is not significant in all cases.

3. Data and testing methodology
3.1 Cross-sectional absolute standard deviations
Following Chang et al. (2000), this study uses cross-sectional absolute standard deviations (CSAD) among individual firm returns within REITs to define the non-linear relation between the level of equity return dispersions and the overall market return.

The CSAD statistic, used as a measure of return dispersion, is formulated as follows:

\[
CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |R_{i,t} - R_{m,t}|
\]

where \( r_{i,t} \) and \( r_{m,t} \) is the return on stock \( i \) and the value of an equally weighted average of all REITs returns for period \( t \), respectively, and \( N \) is the number of stocks in the portfolio. Herd behaviour entails individual investors making investment decisions following the collective actions of the market, and that these actions will lead security returns to converge on the overall market return. Therefore, herd behaviour implies that security dispersions (i.e. CSAD) will decrease with the absolute value of the market return, since each asset becomes similar with regard to sensitivity to the market return.

Chang et al. (2000) suggest that during periods of market stress, one would expect return dispersion (i.e. CSAD) and market return (i.e. \( r_{m,t} \)) to have a nonlinear relationship.
Christie and Huang (1995) suggest that the probability of herd behaviour increases during periods of market stress and large price movements; consequently, we have a benchmark model based on the following quadratic model of return dispersion and market return:

$$CSAD_t = \alpha_0 + \alpha_1 |R_{m,t}| + \alpha_2 R^2_{m,t} + \varepsilon_t$$

(2)

The presence of herding is tested using the following hypotheses:

- **H0.** In the absence of herding effects, we expect in Eq (2) that $\alpha_1 > 0$ and $\alpha_2 = 0$.
- **H11.** If herd behaviour exists, we expect $\alpha_2 < 0$.
- **H12.** If anti-herding behaviour exists, we expect $\alpha_2 > 0$.

Because it is suggested 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; Bikhchandani and Sharma, 2001), we focused on securities that are classified as real estate investment trusts. As mentioned earlier, the choice of REITs was largely motivated by the fact that, to the best of our knowledge, no studies exist on herding among UK REITs. In addition, securitized real estate markets, i.e. REITs, have experienced tremendous growth in the global economy. According to the National Association of Real Estate Investment Trusts (NAREIT), global real estate markets represented more than $1.22tn of equity capitalization in July of 2016. In addition, with REITs being exchange-traded funds that earn most of their income from investments in real estate, REITs have been at the epicentre of research interest because their returns do not suffer from the measurement error and high transaction costs compared with other real estate investments. As indicated by Akinsomi et al. (2016), REITs constitute a very good proxy for the real estate market, while also providing high frequency observable data, since REITs shares trade as common stocks. Because REITs are accessible to all investors, irrespective of their portfolio size, this asset class has been particularly successful in attracting investment capital.

For our analysis, we used daily data comprising 36 primary REITs on the LSE for the period June 2004 to April 2016, with a total of 3070 observations. The source for the closing prices of the various REITs is Datastream of Thomson Reuters. In addition, we considered the FTSE 100 VIX (VIX) in estimating the regime transition probabilities of the Markov-switching model. The VIX data was derived from the same source, with the aim of capturing aggregate equity market uncertainty in the UK.

### 3.2 The TVTP-MS model with VIX

It is argued that the static model in equation (2) leads to a misleading conclusion regarding herd behaviour, as the parameters are assumed to be constant over time (Balcilar et al., 2013a, b; Ngene et al., 2017). To distinguish and examine whether herding behaviour is contingent for different market phases, we estimated the Markov-switching model of the cross-sectional return dispersions for the following three states:

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t} |R_{m,t}| + \alpha_{2,S_t} R^2_{m,t} + \varepsilon_t$$

(3)

where $\varepsilon_t \sim \text{iid}(0, \sigma_{S_t}^2)$ and $S_t$ is a discrete regime variable taking values of \{0, 1, 2\} and following a three-state Markov process. The volatility term in equation (3), $\varepsilon_t$ is modelled to be heteroscedastic with three states such that:
\[ \sigma_t^2 = \sigma_1^2 S_{1t} + \sigma_2^2 S_{2t} + \sigma_3^2 S_{3t} \]  

where \( S_{kt} = 1 \) if \( S_t = k \) and zero otherwise (\( k = 1, 2, 3 \)). The specification of allowing the volatility term to be heteroscedastic differentiates the market regimes in terms of the level of volatility in each regime, i.e. \( \sigma_t^2 = \sigma_k^2 \) for regimes \( k = 1, 2, 3 \) and allows the variance of cross-sectional dispersions to switch across different regimes. In addition, we allowed the regime transition probabilities to be time varying by using the time-varying transition probability Markov-switching model (TVTP-MS) to assess the role of uncertainty in the overall UK equity market in relation to herding regimes in the British REIT market. The main advantage of the TVTP-MS model with regards to the constant transition probability specification is that it allows the duration of herd behaviour to vary across different regimes of market volatility and the gauging of fear and market sentiment, as measured by the FTSE 100 VIX index (VIXUK). Hence after modelling the role of VIXUK shock, we could define the transition probabilities of the Markov chain in equation (3) as:

\[ p_{ij,t} = P(S_t = 1 | S_{t-1} = j, Z_{t-1}) \]

where \( Z_t \) is a vector of exogenous VIX variables.\[ \text{[7]} \]. We could also define \( \theta_{ij} \) as the vector of parameters of exogenous variables associated with the transition probability of switching from state \( j \) at time \( t-1 \) to state \( i \) at time \( t \). The time-varying transition probabilities can be written as:

\[ p_{ij,t} = \Phi(Z_{ij,t-1} \theta_{ij}), \quad i = 0, 1 \text{ and } j = 1, 2, 3 \]

where \( \Phi(\cdot) \) is the normal cumulative distribution function (CDF), and the transition probabilities satisfy \( \sum_{i=0}^{2} p_{ij,t} = 1 \) for \( t = 1, 2, \ldots, T \).

Therefore, we include in the TVTP model the vector \( Z = [z_i] (i = 0, 1, \ldots, 2) \) which is defined as \( Z = (1, \text{VIXUK}) \), with the UK VIX variable being measured in returns.

### 4. Empirical results

This section presents the findings for the TVTP-MS model described in equations (3) through (6). The findings for the static model in equation (2) are reported in Table I. First, we find that coefficient \( \alpha_1 \) in equation (2) is positive and statistically significant, as predicted by the equilibrium model of CAPM, and the cross-sectional absolute deviation of REITs returns with respect to the market return increases with the absolute magnitude of market returns. Second, we find anti-herding behaviour, as illustrated by the statistically significant coefficient \( \alpha_2 \), even though the magnitude is small.

Table II presents our findings for the TVTP-MS model specified in equations (4) through (6). As is evident, the TVTP-MS model is clearly a better fit for the data than is the static

<table>
<thead>
<tr>
<th>( \alpha_0 )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>RSS</th>
<th>logL</th>
<th>AIC</th>
<th>adj.( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6975***</td>
<td>0.7320***</td>
<td>0.03784***</td>
<td>1149.17</td>
<td>-2847.37</td>
<td>1.857</td>
<td>0.8314</td>
</tr>
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**Notes:** The table reports the estimates for CSAD in Equation (2). All estimations were done using the ordinary least squares (OLS) with the Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors. RSS denotes residual sum of squares, log L denotes the log likelihood of the OLS model, AIC denotes the Akaike information criterion, and adj.\( R^2 \) denotes the adjusted coefficient of determination. ***represents significance at the 1% level. A significant and positive \( \alpha_2 \) estimate implies anti-herding behaviour.

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**Table I.** Estimates of the static model
model, as the former has a much lower AIC. This result is not surprising given that we obtained strong evidence (the highest possible level of significance at all possible dimensions involved in the test) of nonlinearity when we applied the Brock et al. (1996, BDS test) to the residuals of the static model (equation (2)). The results are reported in Table AI, in the Appendix of the paper. In addition, we detected as many as four breaks (3 May 2006; 27 May 2008; 2 March 2010; and 16 February 2012) in this equation when we implemented the test of multiple structural breaks, based on the global information criteria as developed by Bai and Perron (2003).

The regime-specific volatility estimates ($\sigma^2_k$, $k = 1, 2, 3$) are reported in Table II. Market regimes are clearly identified in terms of low (i.e. regime 2), high (i.e. regime 1) and extreme volatility (i.e. regime 3) in terms of the level of return, with the low volatility regime being primarily concentrated post the financial crisis, especially in 2011. Our main finding is that there is significant evidence of herding in the UK REITs market in the low volatility regime,
which is opposite to what was detected for the US REITs market by Babalos et al. (2015), who found strong evidence of herding in the crash regime. Our results suggest that in the UK, herding occurs when uncertainty, i.e. volatility is low, with an absence of herding being observed during high and crash regimes of volatility. However, most important is the observation that, unlike the linear static model, the TVTP-MS model detects evidence of herding in a specific regime, namely the low-volatility regime. Thus, our result highlights the importance of modelling nonlinearity when analysing herding behaviour – a result similar to that of Babalos et al. (2015).

In January 2007 the legislation set out the rules for REITs in the United Kingdom. As a result, a number of listed property groups converted to this structure; this change provided opportunities for the growth of the property investment sector because property companies could now get access to capital markets, and investors would have wider investment opportunities than with alternative asset classes, due to the underlying property assets, without significant tax leakage.

Against this background, we carried out a robustness check for the period 2007-2016 to see whether the results are robust before and after 2007; in particular, we found that the results for 2007-2016 are similar compared with the results in Table I. For the TVTP-MS model, the results for 2007-2016 are similar to those for 2004-2016 as seen in Table AII (i.e. our main finding is that there is significant evidence of herding in the UK REITs market in the low volatility regime[9]).

The first break, which occurred on 3 May, 2006, is associated with the implementation of the 2007 rules for REITs in the United Kingdom, when a number of listed property groups converted to REITs. This regime change enabled UK REITs to undertake activities other than those applicable to a property rental business (for example, to be involved in property trading or services where a minimum of 75 per cent of the business comprises a property rental business). The UK REIT regime is set out in Part 4 of the Finance Act of 2006, and the date that Royal Assent received was 19 July 2006, which is one month after the date of the first break, on 3 May 2016. The date (i.e. 27 May 2008) of the second break is associated with the global financial crisis, including the nationalization and splitting of Bradford and Bingley and the part-nationalization of RBS and Lloyds TSB. The date of the third break was 2 March 2010, which is associated with the Corporation Tax Act 2010, Part 12. This Act received Royal Assent on 3 March 2010. The act specified that “no one property or leasehold interest can account for more than 40 per cent of the fair value of the gross assets of the property rental business” and that “In the accounting period, at least 75 per cent of a REIT’s total income-profits (before tax) must arise from its tax-exempt property rental business”. The date of the final break (i.e. 16 February 2012) is also associated with a significant REIT regime change, namely the draft legislation that was published on 29 March 2012. The change reduced the entry barriers and increased the incentives for investors to invest in REITs, which included the abolition of the 2 per cent entry charge for companies converting to REITs.

4.1 Persistence of market regimes
The estimated regime durations in Table II indicate that the low volatility regime is the most persistent, with the longest average duration across market regimes. We observed that the longest average duration of the low volatility regime is 174 days for the All Equity REIT sector. This shows that the low volatility regime is the most persistent, while the average duration for the extreme volatility regime is 14.9 days, as it has the most frequent regime switches. Our findings are consistent with the current literature on herding, using MS models (Balcilar et al., 2013a, b).
The transition probability estimates $p_{ij}$ and its relevant smoothed probabilities, plotted in Figure 1, provide a visual examination of the dynamic nature of regime transitions and herd behaviour in the UK REITs market. The smoothed regime probabilities for the three-regime nonlinear TVTP-MS model is plotted in Figures 1(a) and (c).

The smoothed probability plots generally suggest a low-high-extreme (LHE) volatility transition order, in which the high-volatility regime (i.e. regime 1) follows the low-volatility regime (i.e. regime 2) and the extreme volatility/crash regime (i.e. regime 3) follow the high volatility regime (i.e. regime 1). This finding is consistent with the evidence for advanced markets and provides market regulators with a warning signal before the extreme volatility regime (see, for example, Babalos et al., 2015). It is evident that the crash regime is followed by the high volatility one. Another interesting pattern is exhibited by the fact that from late 2010 the market regime had entered a period of low volatility (regime 2).

4.2 VIX and time-varying transition probabilities
As explained earlier, the parameters, $\theta_{ij}$, $i = 0, 1$ and $j = 1, 2, 3$, in equation (6) capture the dynamic effects of the UK VIX return on transition probabilities across regimes. Significant parameter estimates imply that the VIX plays a role in leading the UK REITs market from one regime to another, possibly driving herding regimes. As described earlier, the $l^{th}$ element of the vector $\theta_{ij}$, that is, $\theta_{ij}$, for $i = 0, 1$ and $j = 1, 2, 3$, is defined as $\{l = 0 \text{ (constant)}, 1 \text{ (VIX}_UK \text{ return)}\}$ with two parameter estimates for the variable.

We find that the $\text{VIX}_UK$ is significant in driving regime transitions in the UK REITs market, as indicated by the significant $\theta_{21,1}$ estimate. Our attention was drawn to the significant transition probability estimates for switching from the high volatility regime (i.e. regime 1) to the low volatility regime (i.e. regime 2), where the herding takes place. We therefore conclude that the UK VIX does play a role in driving regime transition from high to low volatility.

5. Conclusion
Due to globally increasing investment volumes in property, real estate has become an important asset class since the 1990s. The Global Financial Crisis and the recent Brexit shock have also showed that direct and indirect real estate investments in the UK are also highly sensitive to uncertainties. This picture makes it of paramount importance to understand the risk-return characteristics of UK REIT stocks for asset/portfolio managers and policy makers. The market facts also confirm this approach. According to the LSE data, the market value of REITs – involving diversified, specialty, retail, industrial and offices, residential and diversified REITs – is worth £43,544m, and the overall market value of real estate holding and development companies, real estate investment trusts and real estate service sub-sectors is worth £82,386m as of 31 November 2016.[11] Moreover, the British Property Federation and Toscafund Asset Management (2016) estimated that the market value of commercial real estate was £1,662bn, just over 20 per cent of net wealth, and it contributed £94bn to GDP in 2014 in the UK.

As a first in the literature, the study uses static and dynamic models to explore herding in UK REITs over the period June 2004 to April 2016. The study provides various aspects of evidence and interesting implications of herding behaviour in UK REITs.

From a methodology perspective, the study first suggests, in parallel with Babalos et al. (2015), that a TVTP-MS model is a better fit for the data than is the static model. In this respect, the study defines the importance of modelling nonlinearity in herding analyses. Second, given the importance of nonlinearity, the static model, which suggests anti-herding behaviour, is econometrically misspecified. Third, although the static herding model rejects
Figure 1. Return and smoothed probability of three-regime nonlinear TVTP-MS model for UK REITs

(a) $P(S(t) = 1)$

(b) $P(S(t) = 2)$

(c) $P(S(t) = 3)$

(continued)
the existence of herding, the Markov regime-switching model defines three market regimes, namely, the low, high and crash volatility regimes, and it provides evidence of herding behaviour under the low volatility regime but anti-herding behaviour in the high and crash regimes of volatility. In the presence of nonlinearity, the Markov-switching model is clearly the correctly specified econometric framework and should be relied upon to draw inferences. Fourth, the evidence further suggests that the low volatility regime is the most persistent

Figure 1. 

Notes: (a) Smoothed probability: Regime 1; (b) Smoothed probability: Regime 2; (c) Smoothed probability: Regime 3; (d) Time-varying Markov transition probabilities
market regime, with the longest average regime duration involving 174 days, primarily in the post-2011 period (and to some extent before the global financial crisis). Interestingly, this low-volatility herding period essentially coincides with the bull market conditions of the LSE. Fifth, the model results also suggest a low-high-extreme (LHE) volatility transition order, and that the UK VIX does play a role in driving regime transitions from high to low volatility. In this respect, the high volatility regime follows the low volatility regime, and the extreme volatility/crash regime follows the high volatility regime. This herding cycle may translate as a shift from anti-herding behaviour during high volatility regimes to herding behaviour under low volatility regimes.

These results have implications for decisions concerning asset allocation and portfolio diversification in the UK REITs market. First, regarding the order of regime transitions, moving from low to high and to extreme volatility suggests that the market follows a consistent pattern, which warns investors and regulators of potential or imminent extreme volatility in the UK REIT market. This behavioural pattern may provide significant foresight for market participants about changes in REITs returns, depending on the consistent chain pattern in the REITs market. This behaviour in the UK REIT market is similar to those of general stocks in developed markets, where volatility transmits from low to high to crash (Balcilar et al., 2013a, b). This result, however, contradicts the findings of studies on developing markets, such as those of the Gulf States, which shows that the market moves from low volatility to extreme volatility to high volatility (Balcilar et al., 2013a, b). Second, defining the low volatility regime of UK REITs as the most persistent herding market regime in the rising period of the LSE suggests another interesting market insight. This evidence implies that when the general stock market is doing well, which in turn corresponds to low volatility, and hence, lower risks, agents in the REITs sector tend to herd, i.e. to behave similarly. However, when the markets are highly volatile and risky, economic agents operating in the REITs sector tend to behave differently from one another, in an attempt to maximize their profits. Third, the source of the fluctuations in risk in the REITs sector originates from the VIX, i.e. aggregate equity market risks, which spill over into the REITs sector, implying that there are no diversification opportunities between conventional equities and the REITs sector. Therefore, market participants in LSE and UK REITs may perceive that the risk profile in the overall stock market and the property sector may be interconnected.

Overall, the aspects of evidence in this study collectively imply that UK REITs market participants may improve their decision-making by using the herding characteristics and cycles of the REITs market during different volatility regimes, in addition to signals of overall market behaviours from the LSE market index and the UK VIX.

Notes
1. The value of UK REITs was calculated by adding the market capitalization of UK REITs as seen on www.bpf.org.uk/reits-and-property-companies as at 30 September 2017.
2. The market capitalization of the UK REIT market as well as the top five UK REITs were sourced from the LSE. www.londonstockexchange.com/statistics/companies-and-issuers/companies-and-issuers.htm
3. The information was extracted from the FTSE Russell factsheet (the FTSE EPRA/NAREIT global REITs index) as at 29 September 2017.
4. As at April 2016, there were 36 listed UK REITs. Our sample of firms involves listed REITs on the LSE as at April 2016; for instance, our sample includes REITs such as Land Securities group plc, with a market cap of £7.21bn as at September 2017, and Redefine International, an offshore REIT.
with a market cap of £686.64m that trades on the LSE. Our sample size begins with 16 REITs in June 2004 and ends with 36 REITs on 5 April 2016, highlighting the dynamic nature of our data.

5. In this paper, we recognize that the REITs regime begins in 2007. However, we expanded our data to 2004 to extend our timeline: the period from 2004 to 2007 tracks all REITs that converted in 2007; the year 2004 presented a significant count of 16 individual firms for estimating the CSAD. Our robustness tests also examine the REITs regimes solely between 2007 and 2016, and our results remain consistent with earlier results when we use the period prior to REIT conversion, similar to authors such as Akinsomi et al. (2017), who extended and justified the extension of REIT timelines in the case of South African (SA) REITs, which was not investigated due to data constraints. In addition, we ideally needed data at higher frequencies, to pick up herding and to estimate the Markov-switching model precisely, which tends to have a lot of parameters, especially in our case as we allowed for time-varying transition probabilities. In essence, the starting point of 2004 was driven by the need to use high-frequency firm-level data for the REIT’s sector of the UK, which begins only in 2007.

6. Previous studies found that a three-state Markov process fits the stock return model well (Guidolin and Timmermann, 2006; Maheu et al., 2009; Charfeddine and Ajmi, 2013).

7. The variables in $Z_t$ impact the transition probabilities with one lag, since the transition probabilities governing the regime switches that occur from t-1 to t must be determined at time t-1.

8. The TVTP-MS model’s AIC was also lower than that of the MS model, with constant probabilities of transition, having an AIC of 0.4965. Complete details of the results from the MS model’s constant transition probabilities, which were qualitatively similar to those of the TVTP-MS model, are available upon request from the authors. We chose to work with the TVTP-MS model due its better fit and to use the VIX in explaining the movements of the transition probabilities.

9. Detailed results are available upon request.

10. For example, we observed that UK REITs were in the low volatility regime until the beginning of 2007, and then from the beginning 2007 to the middle of 2008, the market return was driven mainly by the global financial crisis. The market was dominated by extreme volatility between the end of 2008 and early 2009.


References


## Appendix

### Table AII.
Estimates for the regime-based herding model for the UK VIX (2007-2016)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>All equity REITs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>0.76431***</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.72106***</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>0.03813***</td>
</tr>
<tr>
<td>RSS</td>
<td>1052.35</td>
</tr>
<tr>
<td>logL</td>
<td>−2424.7</td>
</tr>
<tr>
<td>AIC</td>
<td>2.0088</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.8996</td>
</tr>
</tbody>
</table>

Notes: The table presents the estimates for CSAD in equation (2). All estimations were done using the ordinary least squares (OLS) method with the Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. RSS denotes residual sum of squares, log L denotes the log likelihood of the OLS model, AIC denotes the Akaike information criterion, and adj. $R^2$ denotes the adjusted coefficient of determination. ***represents significance at the 1% level. A significant and positive $\alpha_2$ estimate implies anti-herding behaviour.

### Table AI.
Estimates of the static model (2007-2016)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>All equity REITs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_0$</td>
<td>0.87334***</td>
</tr>
<tr>
<td>$a_1$</td>
<td>1.85006***</td>
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<tr>
<td>$a_2$</td>
<td>0.66114***</td>
</tr>
<tr>
<td>$a_3$</td>
<td>0.73757***</td>
</tr>
<tr>
<td>$a_4$</td>
<td>0.5531***</td>
</tr>
<tr>
<td>$a_5$</td>
<td>0.4751***</td>
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</table>

Herding coefficients

<table>
<thead>
<tr>
<th>Parameter</th>
<th>All equity REITs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{11}$</td>
<td>0.1064***</td>
</tr>
<tr>
<td>$a_{12}$</td>
<td>0.0426***</td>
</tr>
<tr>
<td>$a_{13}$</td>
<td>0.0351***</td>
</tr>
</tbody>
</table>

Regime volatilities

<table>
<thead>
<tr>
<th>Parameter</th>
<th>All equity REITs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_1$</td>
<td>0.0999***</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>1.8448***</td>
</tr>
<tr>
<td>$\sigma_3$</td>
<td>0.01414***</td>
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</table>

Time-varying transition probabilities

<table>
<thead>
<tr>
<th>Parameter</th>
<th>All equity REITs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_{11,0}$</td>
<td>2.7332***</td>
</tr>
<tr>
<td>$\theta_{11,1}$</td>
<td>0.0652</td>
</tr>
<tr>
<td>$\theta_{12,0}$</td>
<td>2.9816**</td>
</tr>
<tr>
<td>$\theta_{12,1}$</td>
<td>−0.2267**</td>
</tr>
<tr>
<td>$\theta_{21,0}$</td>
<td>−1.399***</td>
</tr>
<tr>
<td>$\theta_{21,1}$</td>
<td>0.00140</td>
</tr>
<tr>
<td>$\theta_{22,0}$</td>
<td>6.3322***</td>
</tr>
<tr>
<td>$\theta_{22,1}$</td>
<td>−0.1168</td>
</tr>
<tr>
<td>$\theta_{23,0}$</td>
<td>−2.9491***</td>
</tr>
<tr>
<td>$\theta_{23,1}$</td>
<td>0.0536**</td>
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</tbody>
</table>

Regime durations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>All equity REITs</th>
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</thead>
<tbody>
<tr>
<td>$\tau_1$</td>
<td>14.4</td>
</tr>
<tr>
<td>$\tau_2$</td>
<td>29.6</td>
</tr>
<tr>
<td>$\tau_3$</td>
<td>21.4</td>
</tr>
<tr>
<td>AIC</td>
<td>0.647</td>
</tr>
<tr>
<td>logL</td>
<td>−757.449</td>
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</tbody>
</table>

Notes: This table presents the estimates of the three-regime TVTP-MSH model given in equations (3)-(6). The asterisks ***, ** and * represent significance at the 1, 5 and 10% levels, respectively.
Table AIII. BDS Test on residual of equation (2) (static model)

<table>
<thead>
<tr>
<th>Dimension</th>
<th>BDS statistic</th>
<th>Sth. error</th>
<th>z-statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.0652</td>
<td>0.0020</td>
<td>32.7078</td>
<td>0.0000</td>
</tr>
<tr>
<td>3</td>
<td>0.1203</td>
<td>0.0032</td>
<td>37.9167</td>
<td>0.0000</td>
</tr>
<tr>
<td>4</td>
<td>0.1571</td>
<td>0.0038</td>
<td>41.5370</td>
<td>0.0000</td>
</tr>
<tr>
<td>5</td>
<td>0.1794</td>
<td>0.0039</td>
<td>45.4485</td>
<td>0.0000</td>
</tr>
<tr>
<td>6</td>
<td>0.1907</td>
<td>0.0038</td>
<td>50.0301</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Raw epsilon

Pairs within epsilon

Triples within epsilon

<table>
<thead>
<tr>
<th>Dimension</th>
<th>C(m, n)</th>
<th>c(m, n)</th>
<th>C(1, n-(m-1))</th>
<th>c(1, n-(m-1))</th>
<th>c(1, n-(m-1))^k</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>2634800</td>
<td>0.5597</td>
<td>3310342</td>
<td>0.7032</td>
<td>0.4944</td>
</tr>
<tr>
<td>3</td>
<td>2200863</td>
<td>0.4678</td>
<td>3307738</td>
<td>0.7031</td>
<td>0.3475</td>
</tr>
<tr>
<td>4</td>
<td>1886874</td>
<td>0.4013</td>
<td>3305260</td>
<td>0.7030</td>
<td>0.2442</td>
</tr>
<tr>
<td>5</td>
<td>1649088</td>
<td>0.3510</td>
<td>3302663</td>
<td>0.7029</td>
<td>0.1716</td>
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<td>6</td>
<td>1461537</td>
<td>0.3113</td>
<td>3300162</td>
<td>0.7028</td>
<td>0.1205</td>
</tr>
</tbody>
</table>

Notes: $m$ stands for the number of (embedded) dimensions that embed the time series into $m$-dimensional vectors, by taking each $m$ successive point in the series. The BDS $z$-statistic tests for the null of i.i.d. residuals.

Corresponding author
Omokolade Akinsomi can be contacted at: Kola.Akinsomi@wits.ac.za