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Impact of Volatility and Equity Market Uncertainty on Herd Behavior: Evidence from UK REITs

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Abstract

Employing static/dynamic models that capture herding under different market regimes, we provide novel evidence on the herding behaviour of UK-listed Real Estate Investment Trusts (REITs). Our sample is extensive and covers the period from 30/6/2004 to 5/4/2016. Estimates of herding behaviour are derived using a Markov regime-switching model. The analysis suggests the existence of three market regimes (low, high and extreme or crash volatility) with transition ordered as 'low, high and crash volatility'. Although static herding model rejects the existence of herding in REITs markets, estimates of the regimes switching model reveal substantial evidence of herding behaviours under the low volatility regime. Most interestingly we observe a shift from anti-herding behaviour during high volatility regimes to herding behaviour under low volatility regime, with this caused by the UK VIX.

JEL Classification Code: C32, G11, G15
Keywords: Herd behavior; UK REITs; Markov-switching; Time-varying probabilities.

1. Introduction

The temper of the multitude is fickle.
Machiavelli

Decision making in finance may inevitably involve shortfalls arising from very material reasons such as information asymmetries or market/person specific investment psychology. Literature reveals that irrational features and behavioral aspects of the investment process ranging from non-financial assets to financial assets are among the reasons of anomalies and boom-bust cycles. In this respect, despite well-established theoretical framework and plenty of empirical evidences on efficient market hypothesis, financial markets involve widespread irrationalities. Global/market specific uncertainties/volatilities have also exacerbated irrationalities in the leading/developing financial markets. It is not wrong to expect in the light of past experiences that market and specific investment psychologies may go hand in hand which may result a kind of market-wide roller-coaster effect during up and down market conditions in stock markets. As the signal of a crowd movement reflecting a mass consensus, herd behavior in direct/indirect property investments maybe also analyzed in the context of this irrational/inefficient roller-coaster effect.

Herding behaviour in property stocks has received increasing attention in the property literature. However, the studies, attempt to capture herding behaviours under different market regimes in Real Estate Investment Trusts (REITs), are still at an embryonic stage in the empirical literature. By employing static and dynamic herding models, the study aims to explore herding behaviour in UK-listed REITs over the period of 30/6/2004 to 5/4/2016. As the static modelling, we follow Chang et al. (2000) methodology involving cross-sectional absolute standard deviations (CSAD) among individual firm returns to define non-linear relation between equity return dispersions and

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market return. In addition, we also allow the regime transition probabilities to be time varying by using the time-varying transition probability Markov Switching model (TVTP-MS). Because observation period involves almost 12 years with before and after global financial crisis period, the evidences may imply that UK REITs market may inherently involve long-run and persistent herding patterns. Due to highly sophisticated nature of London Stock Exchange, this behavioral phenomenon provides interesting evidence of herd behavior from a developed market perspective.

The contribution of this study is twofold. Firstly, to the best of our knowledge, this paper is the first study to examine the herding behavior in UK REITs. The intuition behind this investigation is to determine behavioral aspects in decision making in UK REITs connected to the relations among uncertainty, volatility, and herding behavior. Secondly, the study provides critical observation for the role of the different regimes on herding behavior in the UK REIT market. Based on the selected analysis period, we provide a comparative knowledge on herding in low/ high/extreme market regimes. Third, using time-varying transition probabilities of herding behaviours, we also provide significant knowledge on the shifts between positive and negative herding behaviours during different volatility periods. By doing so, we employ a new framework analysing destabilizing effects of herding in UK REIT market. The analysis, providing evidence from a developed country's REIT market, such as UK, may be also found interesting. Because the literature reveals that herding is more likely to take place in emerging markets (Zhou and Anderson, 2013) and emerging markets have been found to accommodate higher herding levels compared to their developed counterparts (Andronikidi and Kallinterakis, 2010). Overall, by focusing on UK REIT stocks before/after global financial crisis, the study opens to debate whether UK REIT stocks show irrationalities from the herding perspective and existing strategies of global portfolio managers and policy-makers are compatible to the herding-based market structure.

The paper has four further sections. Section 2 outlines the previous studies. Section 3 introduces data and testing methodology. The results based on analysis of cross-sectional absolute standard deviations and time-varying transition probabilities are presented in section 4. Finally, the last section is reserved for the conclusion and discussions.

2. Literature Review

As indicated in Keynes' beauty-contest analogy, stock market investments would be driven by the expectations of other investors rather than rational decisions based on analysis about fundamentals of the asset. This animal sprit may typically apparent during bubble (Kindleberger and Aliber, 2005; Akerlof and Shiller, 2009) or herding periods connected to mass psychology and irrational price movements in stock markets. The main consensus in the theoretical herding studies is that herding can be construed as being either a rational or irrational form of investment behavior (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) discuss that herding results from an obvious intent by investors to copy the behavior of other investors and imperfect information, concern for reputation, and compensation structures are the potential reasons for rational herd behavior in financial markets. Devenow and Welch (1996) indicate despite difficult to precisely define, herding could be defined as behavior 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 sun-spot equilibria.

Empirical herding studies focus on either behavior of specific groups (i.e. mutual/pension fund managers, financial analysts) or overall market. For example, by examining the quarterly holdings on 155 mutual funds over the 1975-1984 period, Grinblatt et al. (1995) found relatively weak evidence that mutual funds tended to buy and sell the same stocks at the same time. As the selected studies, 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 evidences on group-wide herding. On the other hand, by analyzing 769 funds and behavior of pension managers, Lakonishok et al. (1992) found no market-wide herding, but weak evidence of herding in smaller stocks and also relatively little of either herding or positive-feedback trading in the largest stocks.

Herding analysis under different market regimes provides interesting country level outcomes. Hwang and Salmon (2004) analyze herding in the US and South Korean stock markets and find evidence of herding towards the market portfolio in both bull and bear markets. The authors further discus that contrary to common belief, the Asian Crisis and in particular the Russian Crisis reduce 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. Analyzing 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 investor 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 context) and extreme market conditions through daily data from the Shanghai and Shenzhen stock exchange markets and found that a bullish context generates a herding behaviour for B-shares while a bearish situation rather favours a crowd movement for A-shares.

As the particular interest of this study, herding in REIT stocks is newly developing research area in the literature. As the first attempt to test herding in the REIT market, Zhou and Anderson (2011) investigated the market-wide herding behavior in the U.S. equity REIT market by utilizing the quantile regression method and found that herding is more likely to be present in the high quantiles of the REIT return dispersion. Authors further discussed that REIT investors tend to herd under turbulent market conditions and herding is more likely to occur and becomes stronger in declining markets than in rising markets implying asymmetry of herding behavior. Moreover, the findings also show that during the global financial crisis REIT investors may not start to herd until the market becomes extremely turbulent. By examining the existence of herding effects in the US REIT market during the period of January 2004–December 2011, Philippas et al. (2013) found that deterioration of investors' sentiment and adverse macro-shocks to REIT funding conditions are found to be significantly related to the emergence of herding behavior and also contrary to common belief 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) explore herding under low/high/extreme volatility market regimes in US-listed REITs during 2/1/2004 and 28/6/2013 and provide evidence about regime switching model reveal substantial evidence of herding behavior under the crash regime for almost all sectors despite static herding model rejects the existence of herding. Moreover, the study suggests a shift from negative herding behavior during low and high volatility regimes to positive herding behavior under crash regime for almost all REITs sectors. Using Markov switching time-varying parameter (MS-TVP) herding model for South African REITs, Akinsomi et al. (2016b) find 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 drives up market volatility, making it especially challenging for policy makers. By

utilizing Chang *et al*. (2000) methodology over the period of July 2007 to May 2016 for Turkish REITs, Akinsomi et al. (2016c) find herding behavior, the presence of directional asymmetry and linear relation between volatility and herding. The authors argue that herding is a persistent phenomenon and increases during the period of market stress in Borsa Istanbul.

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

3. Data and testing methodology

3.1. Cross-sectional absolute standard deviations (CSAD)

Following Chang et al. (2000) this study uses the cross-sectional absolute standard deviations (CSAD) among individual firm returns within REIT 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:

$$CSAD_t = \sqrt{\frac{\sum_{i=1}^{N}(r_{i,t}-r_{m,t})^2}{N-1}} \quad (1)$$

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. The herd behavior assumes that individual investor make investment decision following the collective actions of the market and the actions will lead security returns converge to the overall market return. Therefore herd behavior implies that the security dispersions (i.e. $CSAD_t$) will decrease with the absolute value of market return since each asset become similar in regards to the sensitivity to the market return.

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

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

The presence of herding is tested through the following hypotheses:

H_0: In the absence of herding effects we expect in the Eq (2) that $\alpha_1>0$ and $\alpha_2=0$

H_{11}. If herding behavior are existed we expect $\alpha_2<0$.

H_{12}. If anti-herding behavior are existed 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; and 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 the fact that, to the best of our knowledge, there exists no studies on herding involving 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 $1.22 trillion 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 in the epicentre of research interest since their returns do not suffer from measurement error and high transaction costs compared to other real estate investments. As indicated by Akinsomi et al., (2016a), REITs constitute a very good proxy for the real estate market, providing at the same time high frequency observable data, since REITs shares trade as common stocks. Since REITs are accessible to all investors irrespective of the portfolio size, this asset class has been particularly successful in attracting investment capital.

For our analysis, we use daily data comprising of 68 REITs on the London Stock Exchange for the period 30/6/2004 to 5/4/2016 with a total number of 3070 observations. The source for the closing prices of the various REITs is Datastream of Thomson Reuters. In addition, we consider the FTSE 100 VIX in the estimation of regime transition probabilities of the Markov Switching model. The VIX data is also derived from the same source, and aims to capture 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 misleading conclusion regarding herd behavior as parameters are assumed to be constant over time (Balcilar et al, 2013a, b; Ngene, et al., 2016). In order to distinguish and examine whether herding behavior is contingent on different market phases, we estimate the following three-state Markov switching model of the cross sectional returns dispersions:

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{m,t}\right| + \alpha_{2,S_t}R_{m,t}^2 + \varepsilon_t \tag{3}$$

where $\varepsilon_t \sim iid(0, \sigma_{S_t}^2)$ and S_t is a discrete regime variable taking values in {0,1,2} and following a three-state Markov process[1]. The volatility term in Equation (3), ε_t is modeled to be heteroscedastic with 3 states such that

$$\sigma_t^2 = \sigma_1^2 S_{1t} + \sigma_2^2 S_{2t} + \sigma_3^2 S_{3t} \tag{4}$$

where $S_{kt} = 1$ if $S_t = k$ and zero otherwise (k = 1, 2, 3). The specification of allowing the volatility term in to be heteroscedastic differentiates 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 allow 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 on herding regimes in the British REIT market. The main advantage of TVTP-MS model against the constant transition probability specification is that it allows the herd behavior duration varies across different regimes of market volatility and fear gauge and market sentiment, as measured by the FTSE 100 VIX index (VIX_{UK}). Hence after modeling the role of VIX_{UK} shock we can define the transition probabilities of the Markov chain in Equation (3) as

$$p_{ij,t} = P(S_t = i \mid S_{t-1} = j, \mathbf{Z}_{t-1}) \tag{5}$$

[1] Previous studies find that three-state Markov process fit the stock return model well (see for example, Guidolin and Timmermann, 2006; Maheu et al., 2009; and Charfeddine and Ajmi, 2013)

where $\mathbf{Z}_t$ is a vector of exogenous VIX variables.[2] We can also define θ_{ij} be 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

$$p_{ij,t} = \Phi\left(Z_{ij,t-1}\theta_{ij}\right), \quad i = 0,1 \; and \; j = 1,2,3 \tag{6}$$

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

Therefore, we include in the TVTP model the vector $\mathbf{Z} = [z_i]$ (i=0,1,…,2) in Equation (6) is defined as $\mathbf{Z} = (1, \mathrm{VIX_{UK}})$ with the UK VIX variable 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 1. Firstly, we find that coefficient α_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 is increasing with the absolute magnitude of market returns. Secondly we find anti-herding behavior as illustrated by the statistically significant coefficient α_2, even though the magnitude is small.

Table 2 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 to the data than the static model, as the former has a way lower AIC.[3] This result is not surprising given that we obtained strong evidence (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 have been reported in Table A1 in the Appendix of the paper. In addition, we also detected as many as 4 breaks (3rd May, 2006; 27th May, 2008; 2nd March, 2010; and 16th February, 2012) in this equation when we implemented the test of multiple structural breaks based on global information criteria as developed by Bai and Perron (2003). The regime-specific volatility estimates (σ_k^2, k=1, 2, 3) are reported in Table 2, market regimes are clearly identified in the form of a low (i.e. regime 2), high (i.e. regime 1) and extreme volatility regime (i.e. regime 3) in terms of the level of return volatility, with the low volatility regime being primarily concentrated post the financial crisis, especiall, 2011. Our main finding is that there is a significant evidence of herding for the UK REITs market during the low volatility regime, which is opposite to what was detected for 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 actually occurs when uncertainty, i.e., volatility is low, with anti-herding observed at high and crash-regimes of volatility. However, what is important is the observation that unlike the linear static model, the TVTP-MS model detects evidence of herding in a specific regime, which happens to be the low-volatility regime. Our results, thus, highlight the importance of modeling nonlinearity when analyzing herding behavior – a result similar to that of Babalos et al. (2015).

[Insert Tables 1 and 2 Here]

[2] The variables in $\mathbf{Z}_t$ 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.

[3] The TVTP-MS model's AIC was also lower than that of the MS model with constant probabilities of transition, with the latter having an AIC of 0.4965. Complete details of the results from the MS model 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, as well as the role of the VIX in explaining the movements of the transition probabilities.

4.1. Persistence of market regimes

The estimated regime durations in Table 2 indicates that the low volatility regime is the most persistent with the longest average regime durations across market regimes. We observe that the longest average duration of the low volatility regime is 174 days for All Equity REIT sector. This suggests 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 (see for example, Balcilar and Demirer , 2013)

The transition probability estimates p_{ij} and its relevant smoothed probabilities plotted in Figures 1, showing visual examination of the dynamic nature of regime transitions and herd behavior in the UK REITs market. The smoothed regime probabilities for the 3-regime nonlinear TVTP-MS model was plotted in figures (a)-(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) follows 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[4]. Another interesting pattern is exhibited by the fact that from late 2010 the market regime has 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 UK VIX return on transition probabilities across regimes. Significant parameter estimates imply that VIX play a role in leading the UK REITs market from one regime to another, possibly driving herding regimes. As described earlier, the lth element of the vector $\hat{\theta}_{ij}$, that is $\hat{\theta}_{ij,l}$ for $i = 0,1 \; and \; j = 1, 2, 3$ is defined as $\{l = 0$ (constant), 1 (VIX_{UK} return)$\}$ with two parameter estimates for the variable.

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

[Insert Figure1 Here]

5. Conclusion

Due to globally increasing investment volumes in property, real estate become important asset class since 1990's. Global financial crisis and recent Brexit shock have also showed direct/ indirect real estate investments in UK were also highly sensitive to uncertainties. This picture makes valuable to understand the risk-return characteristics of UK real estate and REIT stocks for asset/portfolio managers and policy makers. The market facts also confirm this approach. According to London Stock Exchange data, the market value of REITs, involving diversified, speciality, retail, industrial & offices, residential, diversified REITs with the 31 companies, is £ 43.544 million and the overall market value of real estate holding & development, real estate investment trusts, real estate services sub-sectors with the 120 companies is £ 82.386 million as of 31 November, 2016.[5] Moreover, British Property Federation and Toscafund Asset Management (2016) estimate that market value of commercial real estate is £1,662 billion, just

[4] For example, we observe that UK REITs were in the low volatility regime until the beginning of 2007 and then from the beginning 2007 to the mid 2008 the market return was driven mainly by the global financial crisis. Since then the market was dominated by extreme volatility between the end of 2008 and early 2009.

[5] Available at: http://www.londonstockexchange.com/statistics/companies-and-issuers/companies-and-issuers.htm.

over 20% of net wealth, and contributed £94bn to GDP in 2014 in UK.

As the first in the literature, the study employs static and dynamic models to explore herding in UK REITs over the period from 30/6/2004 to 5/4/2016. The study provides several evidence of herding behavior in UK REITs. From the methodological perspective, the study firstly suggests in parallel to Babalos et al. (2015) that TVTP-MS model is better fit to the data than the static model. In this respect, the study defines the importance of modeling nonlinearity in herding analysis. Second, static model results mainly suggest anti-herding behavior. It is also defined that cross-sectional absolute deviation of REITs returns with respect to the market return is increasing with the absolute magnitude of market returns. Third, although static herding model rejects the existence of herding, Markov regime-switching model defines three market regimes, as the low/high/crash volatility regimes, and provides evidences of herding under the low volatility regime but anti-herding behavior in high and crash-regimes of volatility. We also find that low volatility regime is the most persistent market regime with the longest average regime durations involving 174 days, primarily in the post 2011 period (and to some extent before the global financial crisis). This low-volatility period showing herding, essentially coincides with the bull market conditions of the London Stock Exchange.

Fourth, the model outcomes also suggest a low-high-extreme (LHE) volatility transition order. 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 behavior during high volatility regimes to herding behavior under low volatility regime. Finally, we also define that UK VIX does play a role in driving regime transition from high to low volatility.

The results have various implications for decisions concerning asset allocation, diversification and collateral value management in UK REITs. First, because REITs returns may reflect the deviations in market return, portfolio/risk managers may expect that return and collateral values of UK REITs may show volatilities depending on the market sentiment in London Stock Exchange and REITs sub-market. Second, UK REITs market participants may take into account the collective movements and market sentiment/psychology are determinative factors of risk-return of UK REITs. In this respect, due to evidences of herding behavior under low volatility regime and also volatility transition order, market participants should be specifically careful about scope and the risks of herding-related irrationalities in UK REITs market during low volatility and volatility transition periods. Third, general uncertainty in the equity market, proxied by the impact of UK VIX, may also provide signal for increasing herding-related risks in UK REITs.

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Table 1. Estimates of the static model

α_1	α_2	α_3	RSS	logL	AIC	adj.R^2
0.6975***	0.7320***	0.0378***	1149.17	-2847.37	1.857	0.8314

Note: The table reports the estimates for CSAD in Equation (2). All estimations are 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 log likelihood of the OLS model, AIC denotes the Akaike information criterion, and adj. R^2 denotes the adjusted coefficient of determination. *** represent significance at the 1% level. A significant and positive α_2 estimate implies anti-herding behaviour.

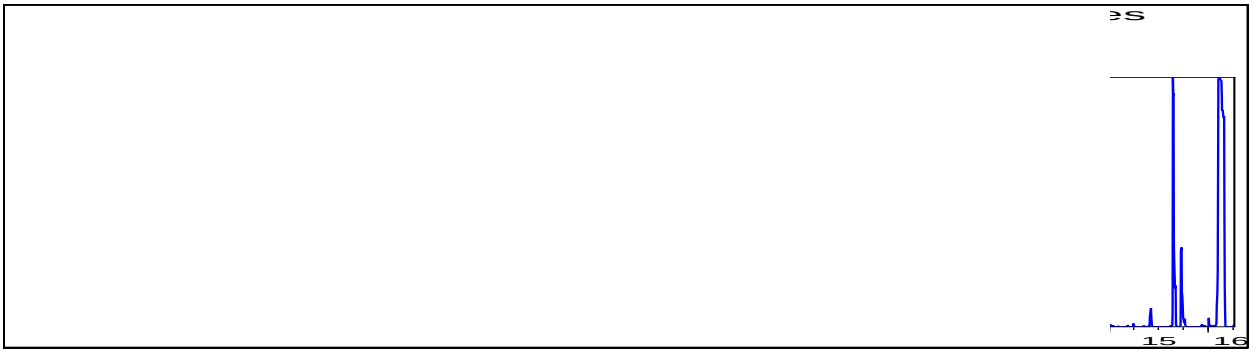
Table 2. Estimates for the regime based herding model with UK VIX

Parameter	**All Equity REITs**
$\alpha_{0,1}$	1.0574***
$\alpha_{0,2}$	0.5746***
$\alpha_{0,3}$	2.1972***
$\alpha_{1,1}$	0.2666***
$\alpha_{1,2}$	0.6346***
$\alpha_{1,3}$	0.0721
	Herding coefficients
$\alpha_{2,1}$	0.0473***
$\alpha_{2,2}$	-0.0734***
$\alpha_{2,3}$	0.1002***
	Regime volatilities
σ_1	0.0700***
σ_2	0.0245***
σ_3	0.8391**
	Time-varying transition probabilities
$\theta_{11,0}$	3.8434***
$\theta_{11,1}$	0.0813
$\theta_{21,0}$	0.8527***
$\theta_{21,1}$	0.1858*
$\theta_{12,0}$	-0.2056***
$\theta_{12,1}$	-0.0379
$\theta_{22,0}$	6.0929***
$\theta_{22,1}$	0.0326
$\theta_{13,0}$	-2.8175***
$\theta_{13,1}$	-0.0597
$\theta_{23,0}$	-4.6643***
$\theta_{23,1}$	0.0223
	Regime durations
τ_1	37.5
τ_2	174.0
τ_3	14.9
AIC	0.431
log L	-643.521

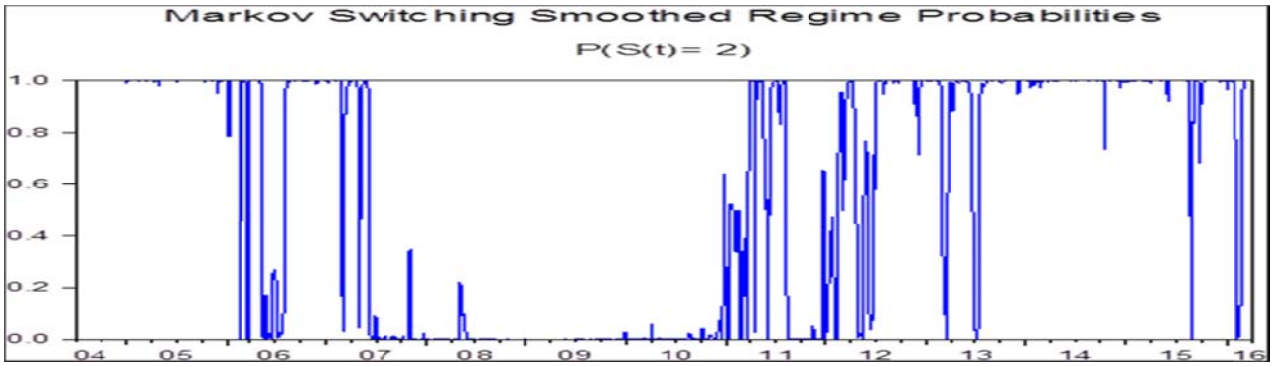
Notes: This table presents the estimates of the three regime TVTP-MSH model given in Equations (3) through (6). The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Figure 1. Return and Smoothed Probability of 3-Regime Nonlinear TVTP-MS Model for UK REITs

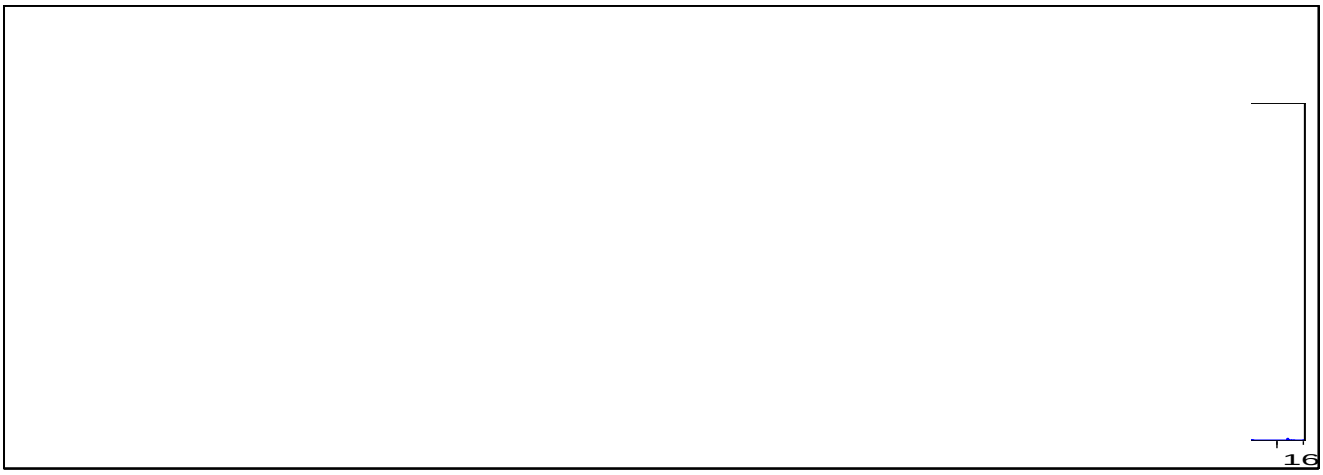
a) Smoothed Probability: Regime 1



b) Smoothed Probability: Regime 2



c) Smoothed Probability: Regime 3



d)Time-Varying Markov Transition Probabilities.

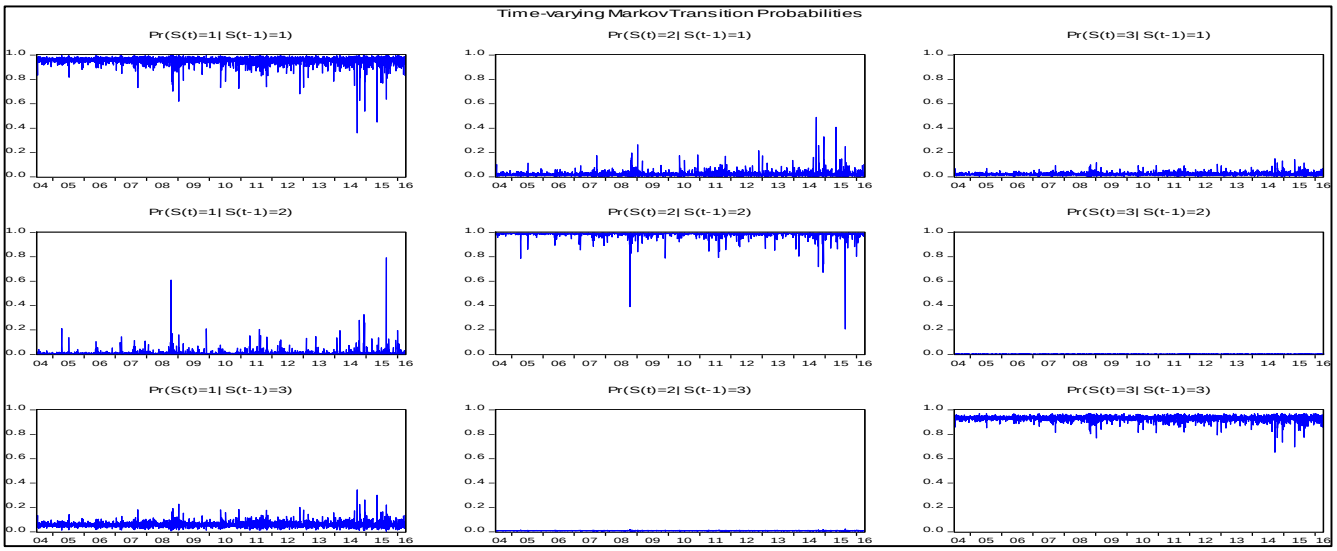


Table A1. BDS Test on Residual of Equation 2 (Static Model)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.0652	0.0020	32.7078	0.0000
3	0.1203	0.0032	37.9167	0.0000
4	0.1571	0.0038	41.5370	0.0000
5	0.1794	0.0039	45.4485	0.0000
6	0.1907	0.0038	50.0301	0.0000

Raw epsilon	0.0058		
Pairs within epsilon	6628888	V-Statistic	0.7033
Triples within epsilon	1.59E+10	V-Statistic	0.5499

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

Note: *m* stands for the number of (embedded) dimension which embed the time series into *m*-dimensional vectors, by taking each *m* successive points in the series. The BDS *z*-statistic tests for the null of *i.i.d.* residuals.