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Revisiting herding behavior in REITs: A regime-switching approach

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Abstract

Employing a dynamic model that captures herding under different market regimes we provide novel evidence on the herding behavior of US-listed Real Estate Investment Trusts (REITs). Our sample is extensive and covers the period from 2/1/2004 to 28/6/2013. Estimates of herding behavior are derived using a Markov regime-switching model. The preliminary analysis confirms 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 regime-switching model reveal substantial evidence of herding behavior under the crash regime for almost all sectors. Most interestingly we observe a shift from negative herding behavior during low and high volatility regimes to positive herding behavior under crash regime for almost all REITs sectors.

Keywords: Cross Sectional dispersion**;** Herding; REITs; regime switching

JEL Classifications: C32, G11, G15

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1. Introduction

It has long been recognized that housing developments are irrevocably associated with the crisis that has severely hit financial markets and global economy since August 2007. Starting in late 1990s the housing market in US and in other developed countries experienced an unprecedented housing boom coupled with loose monetary policy and credit expansion. A series of market developments such as vigorous financial innovation, improper risk management, lack of transparency, moral hazard and increasing leverage have favored in one or another way the creation and the bust of the bubble. Asset price bubbles can be the result of herding behavior by institutional investors as several studies point out (see inter alia Friedman, 1984, Dreman, 1979). Herding is broadly perceived as an exuberant and irrational synchronized movement of asset prices which is not justified by their fundamental values. Nofsinger and Sias (1999) in their seminal study define herding as trading in the same direction by a group of investors for a period of time. Herding entails significant implications both for regulatory authorities and investors. In particular, during periods of market stress, herding behavior poses significant threats to the financial fragility (see Demirer and Kutan, 2006 and Shin, 2010).

Although it has gained a lot of prominence among researchers herding is still masked with an ambiguity in terms of magnitude and observed patterns. Literature classifies herding behavior into two broad categories namely intentional, and unintentional or spurious. In the former case, investors tend to neglect their own private information and intentionally imitate the actions of the others assuming that they possess superior information whereas in the latter case unintentional herding refers to market-wide homogeneous reaction to readily available information and signals (see inter alia Bikhchandani & Sharma, 2001). However, herding does not always constitute an irrational investment behavior. For example, as Bikhchandani and Sharma (2001), point out a rise in interest rates could lead investors to reduce their portfolio equity exposure since stocks have become less attractive compared to fixed-income securities. This situation is described as a fundamentally-driven spurious herding behavior.

Herding is a very interesting phenomenon to explore that entails serious implications for investors and market regulators. Additionally, in periods of market turbulence, herding behavior may lead to inefficiency, cause excessive volatility, enhance financial fragility and generally disrupt the productive flow of funds within the financial system through irrational pricing. Gathering on the same side of the market can also intensify the co-movement among asset returns, and hence cast doubt on the benefit of portfolio diversification (Baur, 2006; Chang et al., 2000; Chiang & Zheng, 2010; Morelli, 2010).

Literature on herding behavior maps its way into two different paths. On the one hand there are studies that examine group-wide herding that is correlated actions among certain groups of investors, such as mutual fund managers and financial analysts. Measuring herding in this way requires detailed data on the transactions of specific group of investors. Lakonishok et al. (1992) were the first to examine group-wide herding introducing a widely employed transaction-based herding measure. Their analysis was conducted for a sample of US pension fund managers and documented no significant pattern in their trading actions. Other studies in this specific area include Kremer & Nautz (2013), Clement and Tse (2005), Gleason and Lee (2003), Graham (1999), Trueman (1994), Welch (2000), and Wermers (1999). However, the majority of the relevant studies explores the existence of herding behavior by monitoring the shifts of stock returns dispersion in response to market movements. The theoretical foundations of this test were put forward by Christie and Huang (1995) who argued that herding reveals itself as a market-wide phenomenon causing a common response of asset prices irrespective of available information. Therefore, Christie and Huang (1995) pointed out that whenever cross-sectional dispersion in individual stock returns diminishes herding is detected. On the other hand, when cross-sectional dispersion of stock returns increases we observe the so-called anti-herding behavior. A series of studies have employed the above measures in order to explore herding effects in the US market (Christie & Huang, 1995) and in international markets as well. In particular Chiang et al. (2010), Demirer and Kutan (2006), Tan et al. (2008), investigated the existence of herding effects in the Chinese stock markets whereas Chiang and Zheng (2010) examined a large sample of 18 markets. In a related study, Gleason et al. (2004) examined herding in the US market by employing data on nine sector S&P 500 Exchange Traded Funds (ETFs) listed on the American Stock Exchange. Along the same lines Economou et al. (2011) provided evidence of herding behavior for four south European markets whereas Zhou & Anderson (2013) and Philippas et al. (2013) examined the existence of herding effects in the US REITs market. Recently, Galariotis et al. (2014) attempted to explain the herding behavior of US & UK leading stocks using macroeconomic variables.

Despite their wide use the traditional methods that can be found in the seminal studies of Christie and Huang (1995) and Chang et al. (2000), have been in the epicenter of intense criticism. In particular, these tests are static and thus fail to explicitly accommodate the dynamic nature of the observed pattern. Along these lines and following the suggestions of Hwang and Salomon (2004), contemporary research on the field has focused on a time-varying measure of herding. Balcilar et. al., (2013) who used the regime switching approach, Gębka and Wohar (2013) who relied on quantile regressions and Klein (2013) who utilized Markov switching seemingly unrelated regressions are among the few recent studies that employ dynamic approaches. Also, a number of studies (Chiang et al., 2010; Christie & Huang, 1995; Economou et al., 2011; Gleason et al., 2004; Goodfellow et al., 2009, for Polish individual investors; Henker et al., 2006) report situations of excessively high cross-sectional return dispersion, which was termed by Gębka and Wohar (2013) "negative herding".

The causal nexus between residential market and the macroeconomic environment in either direction has gained a lot of prominence in the literature (for an excellent review see Agnello & Schuknecht, 2011). A significant component of household expenditure as well as total wealth consists of residential real estate. Substantial variability of residential property prices would suggest significant variability in wealth, and thus potentially significant household wealth effects. Therefore, REITs provide an ideal setting for research due to their unique characteristics and nature. In fact as several studies claim (see inter alia Zhou and Lai, 2008 and Lee and Chiang, 2010), REITs are appropriate research candidate for the real estate market because their assets are mainly invested in real estate property.

Real Estate Investment Trusts (REIT) were established in 1960 and ever since has become a rather popular investment vehicle inside and outside the USA. REITs owe their success mainly to their unique characteristics such as diversification, liquidity and regular income in the form of dividends[1]. A REIT can be defined as a corporate entity that gathers available funds from individual investors and invests them in income-generating real estate. Many REITs have their shares traded in major stock exchanges. In the case of REITs, it was the first time that the benefits of large-scale commercial real estate investment were accessible to all investors other than to large financial intermediaries and to wealthy individuals. Gradually, the benefits of this new investment product caught the attention of investors and almost 50 years after their launch almost 178 REITs are traded in New York Stock Exchange with a total market capitalization of more than $700 billion. REITs are classified into two broad categories namely equity and mortgage trusts. Equity REITs are the most common type and their main purpose is the ownership and operation of income-generating real estate. On the other hand mortgage REITs mostly earn their revenues through real estate financing.

With the above in mind and in view of the growing popularity of Real Estate Investment Trusts (REITs) this paper proposes a novel herding model that accounts for high- and low-

[1] REITs are obliged to pay out at least 90 percent of their taxable income as dividends to shareholders.

variance regimes through a Markov regime-switching model. Our analysis focuses not only on the two broad categories of US equity and mortgage REITs but on specific subsectors of the equity category such as health, lodging (hotel), industrial, mortgage, residential, retail and diversified. This distinction is important considering that REITs are growing in popularity and number.

Our analysis is different from earlier studies in several ways. Firstly, we extend earlier findings of Philippas et al. (2013) and Zhou & Anderson (2013) on US REITs market. On methodological grounds, we propose a Markov-switching (MS thereafter) herding model where the cross sectional absolute dispersion of REITs returns is allowed to follow multiple regimes. Most studies that use stochastic regime-switching to model stock returns utilize a two state or two regime MS model. Considering the switching impact of macroeconomic fundamentals due to business cycles, a two-regime model representing recessionary and expansionary periods can be considered natural. However, in this study, we use a more general approach and allow three regimes in the MS model as warranted by formal tests. The three-regime specification allows us to represent market states by low volatility, high volatility, and crash market conditions where each regime is associated with different mean returns and variances.

Previewing our results we document the existence of three market regimes (low, high and extreme or crash volatility) with transition ordered as 'low, high and crash volatility'. Proper statistical tests conducted confirm that the crash regime is a true regime and not a statistical artifact. Although static herding model fails to establish the existence of herding behavior in REITs market estimates of the regime-switching model reveal substantial evidence of herding behavior under the crash regime for the market as a whole and for almost all sectors. Most interestingly we observe a shift from negative herding behavior during low and high volatility regimes to positive herding behavior under crash regime for almost all REITs sectors. Sector level analysis reveals that herding phenomena are mostly concentrated around 2009 and early 2010 almost in all sectors with some notable exceptions.

The remainder of the paper is structured as follows. Section 2 describes the data and the methodology employed while Section 3 presents the results and the relevant discussion. The concluding remarks are provided in Section 4.

2. Methodology and Data

2.1 Data

Daily returns of all US equity REITs listed on NYSE, AMEX and NASDAQ have been calculated for the period 2/1/2004 to 28/6/2013 with a total number of 2389 observations. The source for the closing prices is Thomson Reuters Datastream. In order to avoid any survivorship bias we have included both active and dead REITs that are contained in the reports of the National Association of Real Estate Investment Trusts (NAREIT).

In order to compute the relevant dispersion measure namely Cross Sectional Absolute Deviation (CSAD) we must first calculate the market portfolio return $R_{m,t}$. Thus, following relevant studies the equally-weighted average of the available REITs returns on the corresponding day is employed as a proxy for the market portfolio return ($R_{m,t}$). Apart from the REITs market as a whole we examine the herding effects for every market segment individually. Equity REITs are classified into eight property sectors including Industial/Office (IO), Retail (R), Residential (RES), Health Care (H), Lodging/Resorts (LR), Diversified (D), Specialty and Self Storage (Other). Moreover, we also include Mortgage (M) REITs. To this end we calculated the equally-weighted average return and CSAD measure for each sector.

The descriptive statistics for the CSAD measure and daily returns are reported in Panel A and B respectively of Table 1. In the case of return dispersions (reported in Panel A) Mortgage REITs exhibit the highest standard deviation, suggesting higher variability across stock returns in this sector compared to other REITs sectors. This may also imply that the stock return in the Mortgage sector experienced unusual cross-sectional variations due to unexpected news or shocks which, again, can be related to the events that recently unfolded in the US mortgage industry. On the other hand, the Health Sector exhibits the lowest variability. Examining the sector returns presented in Panel B we notice that Equity REITs in general exhibited a positive average return whereas Mortgage REITs probably for the reasons already stated experienced a negative average return. Within the Equity REITs there are four sectors with positive returns (Retail, Residential, Health Care, Other) and three sectors that suffered losses (Industrial/Office, Lodging/Resorts, Diversified) during the analyzed period. As for the most volatile sector we document Lodging/Resorts sector while Other sector has the lowest volatility.

2.2 Methodology

2.2.1 Static model of herding behavior

In our baseline model we employ the most widely used measure of dispersion of returns in the literature, the CSAD measure that is calculated as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \qquad (6)$$

where $R_{m,t}$ is the value of an equally weighted average of all REITs returns. The nonlinear relationship, in case of herding phenomena is described by the following equation:

$$CSAD_t = \alpha_0 + \alpha_1\left|R_{m,t}\right| + \alpha_2 R_{m,t}^2 + \varepsilon_t \qquad (7)$$

Presence of herding is tested through the following hypotheses:

H$_0$. *In the absence of herding effects we expect in the model* $\alpha_1 > 0$ *and* $\alpha_2 = 0$.

H$_1$. *If herding effects are encountered we expect* $\alpha_2 < 0$, *otherwise if* $\alpha_2 > 0$ *anti-herding behavior occurs.*

2.2.2 Herding behavior under regime switching

After examining any herding behavior of the US REITs assuming constant parameters throughout the estimation period we distinguish between the different market phases where herding behavior may or may not occur in one or another of these phases. To this end, the following three-state Markov switching model of the cross sectional returns dispersions is estimated:

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

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. Thus, the random variable S_t is defined as a 3-state first order Markov chain. The specification is fulfilled by defining the transition probabilities of the Markov chain as $p_{ij} = P(S_{t+1} = i \mid S_t = j)$. Thus, p_{ij} is the probability of being in regime *i* at time t+1 given that the market was in regime j at time t, where i and j take values in $\{0,1,2\}$. The transition probabilities satisfy $\sum_{i=0}^{2} p_{ij} = 1$.

Modeling stock returns by means of Markov Switching (MS) models is encountered in numerous studies, including Tyssedal and Tjostheim (1988), Hamilton (1988), Schwert (1989), Pagan and Schwert (1990), Sola and Timmermann (1994), Schaller and van Norden (1997), Kim, et al. (1998), Kim and Nelson (1998), and Mayfield (1999). The superiority of MS models compared to linear models lies in their advantage to track patterns beyond traditional stylized facts, which only nonlinear models can generate. Generally speaking, nonlinearities in stock returns owe their existence to: (i) speculative behavior of market participants giving rise to fads, bubbles and market crashes; and (ii) fundamental macroeconomic factors, which are inherently characterized by regime-switching related to business cycles. The underpinnings of regime-switching in stock returns including the rational stochastic bubble model of Blanchard and Watson (1982) and the switching fundamentals model can be found in the asset pricing model of Ceccheti et al. (1990).

The three novelties of the MS herding model given in Equation (3) which were indicated briefly earlier are discussed in more detail as follows. First, the cross sectional absolute dispersion of REITs is allowed to follow multiple regimes. Most studies that use stochastic regime-switching to model stock returns utilize a two state or two regime MS model. Considering the switching impact of macroeconomic fundamentals due to business cycles, a two-regime model representing recessionary and expansionary periods can be considered natural. However, in this study, we use a more general approach and allow three regimes in the MS model specified in Equation (3) as warranted by formal tests. The three-regime specification allows us to represent market states by low volatility, high volatility, and crash market conditions where each regime is associated with different mean returns and variances. Evidence obtained in this study as well as in several studies including Cakmakli et al. (2011), Guidolin and Timmermann (2006), Maheu et al. (2009), Chen and Shen (2012) for the REITs market suggests that multiple regimes might be required to adequately capture the dynamics of stock returns. The evidence obtained in Cakmakli et al. (2011) shows that in addition to two regimes for the bull and bear markets, there can be additional regimes that are needed to capture crashes and recoveries (Guidolin and Timmermann, 2006), or bull market corrections and bear market rallies (Maheu et al., 2009). Second, our MS specification fully allows for regime-specific volatilities by specifying regime-dependent heteroskedasticity. Indeed, regime-dependent volatilities are crucial for accurate identification of regimes for stock markets. Therefore, our model distinguishes between different market states by allowing for different levels of market volatility. Thus, the major distinction across the bear, bull and speculative markets relates to the level of volatility and the sign of returns as there are negative returns during bear markets and positive during bull and speculative markets, which is consistent with Maheu and McCurdy (2000) and Guidolin and Timmermann (2006). Finally, we further allow all parameters of the model to vary across regimes and not only the variance.

3. Empirical results

3.1 Herding based on the static model

We begin our analysis with the first set of empirical tests examining the existence of herding effects in REITs in the context of model (2). Estimation results for the static model are reported in Table 2. When all equity REITs are considered the cross-sectional absolute deviation of REITs returns with respect to the market return is increasing with the absolute magnitude of market returns (coefficient α_1 in model (2) is positive and statistically significant as predicted by the equilibrium model of CAPM). Stated differently, the results of the nonlinear model reveal the absence of herding behaviour as illustrated by the statistically insignificant coefficient α_2. Our finding contradicts that reported by Philippas et al. (2013) who documented significant evidence of herding in the US REITs market. As expected, the coefficients of the market return (R_m) are found to be significant and positive for all REITs sectors. An explanation for this result lies in the cross-sectional diversity of REITs betas, resulting in greater dispersion as every stock reacts differently to the market return movement. The results for the various sectors reveal an interesting degree of heterogeneity in the case of the estimates for the herding coefficient (α_2). In particular, the static model yields statistically significant negative estimates of the α_2 coefficient for several sectors including the Industrial/Office, Retail, Health Care, Lodging/resorts & Diversified sectors but the coefficient is statistically significant only for the Industrial/Office sector. The results for this sector clearly suggest that stock return dispersion is reduced during periods of large market movements, which is consistent with Hypothesis 1 of herding behavior. On the other hand, the CSAD of three sectors namely Residential, Other and Mortgages carries a positive but insignificant coefficient to squared term of market return. Our results for the individual REITs sectors are again in contrast to those of Philippas et al. (2013) who detected evidence of herding in the Diversified, Lodging/ Resorts, Industrial/ Office and Retail sectors. However, they did not report any evidence of negative herding behaviour (positive and statistically significant α_2 coefficient) in any sector whatsoever.

Finally, the explanatory power of the static model for CSAD as expressed by the adjusted R^2 ranges from 42.61% to 66.01%.

3.2 Herding under different regimes

In this section, we examine the herding behavior of US REITs assuming three different regimes of the market. Since the number of regimes is a priori known we estimate the parameters of the MS herding model in Equation (3) and the likelihood of each model is evaluated using the filtering procedure of Hamilton (1990) followed by the smoothing algorithm of Kim (1994). The log-likelihood of the MS model is a function of the parameters in Equation (3) and the transition probabilities. The estimates are obtained by maximizing the log-likelihood subject to the constraint that the probabilities lie between 0 and 1 and sum to unity. The expectation maximization (EM) algorithm of Dempster et al. (1977) is usually employed for the maximization of the log-likelihood. Though, in the present study the feasible non-linear programming approach of Lawrence and Tits (2001) is preferred due to its effectiveness and faster convergence.

Before we proceed with the estimation of the model it is standard procedure for the construction of MS models suitable to identify a feasible set of candidate models. There are two parameters the number of regimes (k) and the specification of variance that will determine the set of models to consider. In our empirical setting both regime-independent variance models, MS(k), and regime-dependent variance (heteroskedastic) models, MSH(k) are considered. When we estimate a specific MS model we then go a step further to test for the presence of nonlinearities in the data. It is crucial to establish whether the inclusion of a nonlinear term results in a superior model compared to the linear constant coefficient (static) model in Equation (2). It should be noted that in the case we wish to compare the MS model against the linear alternative, or a k regime model against a (k-1) regime model, the transition probabilities are not known under the null hypothesis and, thus, the standard distribution theory does not hold. To resolve this, Ang and Bekaert (2002), using Monte Carlo evidence, claimed that the test based on the likelihood-ratio statistic between the estimated model and the derived linear model follows approximately the $\chi 2(q)$ distribution, where q equals the number of restrictions plus the nuisance parameters, i,e., free transition probabilities, that are not specified under the null. In our results we present p-values both based on the conventional χ^2 distribution with q degrees of freedom and also the approximate upper bound for the significance level of the LR statistic as derived by Davies (1987). When the presence of nonlinearity in the data has been diagnosed, the next step is to decide on the number of regimes and the type of MS model relying on both the likelihood-ratio statistic as calculated earlier and the Akaike information Criterion (AIC). Moreover, our empirical procedure is consistent with Psaradakis and Spagnolo (2003) and Krolzig (1997) who suggested the use of AIC for accurate inference of the number of regimes and the type of the MS model. Related to the above, Psaradakis and Spagnolo (2003) using Monte Carlo experiment confirmed that AIC yields reliable results when it comes to model selection.

The calculated log likelihoods and AICs for the static model and for candidates of herding models, 2- and 3-regime heteroskedastic MSH variants and homoskedastic MS candidates are reported in Table 3. The log likelihoods reported in Table 3 are next used as inputs for the calculation of the LR tests which are presented in the first panel of Table 4. Both the standard and Davies LR tests strongly reject the linear static herding model for all REITs sectors. Thus, all four candidate models of the nonlinear MS herding models are strongly supported against the static model, establishing substantial evidence against the linear herding model in all REITs sectors.

Since we have confirmed indisputable evidence against the linear model, we set out to decide on the type of the MS model and the number of regimes. To this end, both the AIC and LR tests are employed. The lowest values of AICs that is reported in the second panel of Table 3 are observed for the 3-regime and regime-dependent variance model MSH(3).

Following the previous analysis in the second panel of Table 4, explicit tests for testing the regime-dependent variance models and the 2-regime models against the 3-regime models are reported. Observing the LR tests we infer that MS(3) models are strongly favored against MS(2), and MSH(3) against MSH(2) at the 1 percent level either with the traditional or Davies tests and for all sectors. Overall, the regime-independent variance models MS(k) are strongly rejected in favor of the state-dependent variance models MSH(k) for all sectors. As illustrated in the formal test results in the second panel of Table 4 and in the AIC values in the second panel of Table 3, there is substantial evidence in favor of the MSH(3) models for all REITs sectors, confirming the existence of three market regimes for these US REITs stock returns.

However, it could be the case that the third regime is spurious and is induced by a number of spikes in the data. For example, Nielsen and Olsen (2001) concluded that the third regime for Danish stock market was data sensitive and ceased to exist when they added dummy variables to their model as an attempt to capture few spikes in the data. Along the same lines and as a robustness test for the three-regime specification, we include into our model several combinations of dummies that address certain spikes in the CSAD values exceeding three standard deviations of the mean, with the restriction that no more than eight dummies will be included in any case. The three-regime results exhibited in Table 4 remain unaffected under all of the dummies combinations. In fact, after including the dummies it is observed an amplification of the test results in favor of three market regimes in some cases. Thus, the selection of a three-regime specification for these sectors is fully justified and conforms to real regimes. The three-regime specification receives even greater support if we observe the estimates of parameter n_2 reported in Table 5. Thus, estimates of n_2 which measures the percentage of observations corresponding to the crash regime ranges between a low of 6.91% (for Diversified sector) and high of 19.25% (for Industrial/Office sector) of the total observations.

Estimates for the three-regime herding model are reported in Table 5. It is important to note that the three regimes are easily distinguishable from the estimated levels of the volatility terms (σ^2) for each state. For example, in the case of All Equity REITs the estimated variance value of 0.4710 in regime 2 (crash regime) is 10 times as high as the variance estimate of 0.0468 for regime 0 (low volatility regime), which confirms the existence of more than one market regime. Significant evidence of herding is detected for all REITs sectors during the crash regime. A possible explanation is that investors discard their own information and choose to mimic institutional investors during high market stress periods and thus herding is more prevalent during the crash regime than in the other two regimes. Comparing the results of the regime-switching model to those reported for the static model we infer that the static model fails to capture herding under periods of high market stress. Our findings are aligned with previous studies such as Christie and Huang (1995) and Chang et al. (2000), suggesting that investors will be more likely to discard their own information and mimic the actions of others during periods of market stress. Therefore, the regime-switching framework appears to capture the dynamic behavior of herding phenomenon and fits into the logic behind the testing methodology of herding which is built on the relationship between return dispersions and market returns during periods of market stress. The other noteworthy observation from the estimates of the regime-switching model is the detection of significant evidence of negative herding (or anti-herding behavior) for almost all REITs sectors at regime 1 and 2 as illustrated by the statistically significant positive coefficients $\alpha_{0,2}$ and $\alpha_{1,2}$. In order to explain the appearance of negative herding Gebka and Wohar (2013) provide three different behavioral-based explanations: localized herding, excessive "flight to quality", and investors' overconfidence.

The previous evidence motivates us to scrutinize the MS herding model estimates as related to the transition probability estimates p_{ij} that are reported in Table 5 and the relevant smoothed probabilities plotted in Figures 1-5. Our attention is firstly drawn to the transition probability estimates for switching from the crash regime to the low volatility regime, p_{02}, which is essentially zero except for the All Equities and the Industrial/Office sector. On the other hand the probability of switching from switching from crash regime to high high volatility regime, p_{12}, varies from 2.10% to 20.02%. This finding clearly implies that in most of these markets there is a smooth transition from crash to low volatility regime and high volatility regime appears right after crashes.

In all REITs sectors, we observe a significantly low transition probability pattern from low to high volatility, p_{10}, ranging from 2.32% for Retail sector to 8.28% for Residential sector. This finding reveals a situation where a crash is essential step to shift from low to high volatility for these sectors. The previous finding is further supported by the much higher transition probability (p_{12}) estimates of switching from crash regime in one period to high volatility in the next, ranging with the exception of All Equity and Residential from 2.1% (All Equity) to 20.02% (Diversified sector). Our results are consistent with those reported by Balcilar et al. (2013) for the GCC stock markets.

A very useful conjecture that follows the previous analysis is that the order of the three regimes in REITS market is low volatility, high volatility and crash. This is supported by estimates of the probability for switching from the low volatility regime to the crash regime, $p_{20,}$ which are mostly zero or very close to zero except Industrial/office sector for which the estimate is 2.01%. Moreover, the probability of switching from high volatility regime to crash regime, p_{21}, ranges between 0.63% and 5.17%. Combined with the chronological orders of the regime periods in Figures 1-9, we conclude that the regime transition in REITS market is generally from low volatility to high volatility, high volatility to crash, crash to high volatility, and high volatility to low volatility. Balcilar et al. (2013) pointed out this structure is the transition structure for developed stock markets which has the common order "low, high, crash volatility' that serves as a "warning light" of an imminent crash expected to follow periods of market turbulence.

Next from the estimates of the MS model in Table 5 we observe that the average duration of the crash regime ranges from a low of 5.32 days for Diversified sector and a high of 39.17 days for All Equity sector. Clearly these figures suggest a transient nature of the crash regime that requires no action from policy makers. However, the crash regime is highly persistent for some of the REITs sectors. For example, we refer to the 96.26% probability of Retail sector to be in the crash regime given that it was in same regime the previous period. Average duration for the low volatility regime ranges from 15.75 days (Residential sector) to 51.07 days (Retail sector). Finally the lower bound of average duration for high volatility regime is 6.71 days for the Diversified sector and the upper bound is 20.67days for the Health Care sector.

In order to get a better insight of the structure of the regimes we can observe the smoothed probability estimates depicted in Figures 1-5. Smoothed probability estimates serve as an alternative view of the transition probabilities. Examining the evolution of smooth probabilities we can obtain a perspective view of how regimes are structured over time. Generally speaking, a regime change is marked by the gray areas in the figures and consistent with the findings of Balcilar et al. (2013) we find that the crash regime is followed by the high volatility for many sectors. For example, we observe that Mortgage REITs were in the low volatility regime until the mid of 2007 and then from mid 2007 to mid 2008 driven mainly by the outburst of the US subprime mortgage crisis the volatility of mortgage sector increased. Then, a crash regime emerges at the end of 2008 and early 2009, each of which is followed by the high volatility regime. Another interesting pattern is exhibited by the Residential sector which is a subsector of the Equity REITs and has been severely hit by the repercussions of the global financial crisis. In particular, this sector has been repeatedly in the high volatility regime until mid of 2008 when the crash regime makes its appearance and it is followed by the high volatility regime. Interestingly, from late 2010 this sector has entered a period of low volatility (regime 0). However it should be noted that the All Equity REITs category along with two subsectors (Industrial/Office, Retail) exhibits a different pattern. In particular, the order of the volatility regimes for these markets is the following: low volatility, high and crash regime and then the crash regime is followed again by the high volatility regime. Indeed, as Figures 1 (b to d) illustrate All Equity REITs experienced low variability for a long period from 2004 until the late 2007, then a regime of high volatility was established from late 2007 until late 2008 and then (late 2008- mid 2009) there was a crash regime that was again followed by a high volatility regime.

Panels (a) in Figures 1 through 5 display returns, along with periods when herding is observed. The results draw a similar picture for the majority of REITs sectors. Herding is mostly concentrated around 2009 and early 2010 almost in all sectors with some noteworthy exceptions. In Figure 1(a) we observe that herding is intense in the All Equity sector from the beginning of 2009 to early 2010 when the repercussions of the global financial crisis escalated. Interestingly, herding is not observed in the low volatility regime or in the high volatility regime. As for the rest of the sectors, in Figure 2(a) we observe that the Industrial/Office sector experienced persistent herding during certain periods in late 2006, late 2007, and early 2008 and from late 2008 to mid 2009, from mid 2012 to end of 2013. Finally, Residential and Mortgage sector display herding for longer periods probably due to their direct relation with the mortgage market that was in the epicenter of the recent global financial crisis.

4. Conclusions

Motivated by the pivotal role that real estate might have played in the unfolding of the recent global financial crisis and the increased volatility that has plagued the financial markets this study proposes a variant of the standard test model and employs a new herding model that accounts for herding behavior of REITs under different market regimes. REITs provide an ideal setting for research due to their unique characteristics and nature. In fact as several studies claim (see inter alia Zhou and Lai, 2008 and Lee and Chiang, 2010), REITs are appropriate research candidate for the real estate market because their assets are mainly invested in real estate property. Therefore, we focus on an extensive sample of US-listed Equity and Mortgage REITs for the period 2/1/2004 to 28/6/2013 and estimate a three-state Markov-Switching (MS) model for the cross sectional dispersion of REITs returns. In contrast to static models our alternative specification allows us to draw inferences regarding herding behavior under different market phases. Relevant studies on the stochastic behavior or REITs returns (Chen and Shen, 2012) or the existence of bubbles in the REITs market (Paskelian et al., 2011) reinforce our choice of the variance-dependent model in order to explore herding behavior.

Consistent with previous studies (Christie and Huang, 1995, Chang et al., 2000) the results from the regime-switching model provide evidence of substantial herding for all REITs sectors only during the crash regime. Herding is mostly concentrated around 2009 and early 2010 almost in all sectors with some noteworthy exceptions. Interestingly, herding is not observed in the low volatility regime or in the high volatility regime. On the contrary, estimates of the regime-switching model favor the existence of negative herding (or anti-herding behavior) for almost all REITs sectors at regime 1 and 2. Interestingly, results of the static model confirm the absence of herding behavior for all but one sector (Industrial/Office).

Importantly, our results reveal the existence of three market regimes (low, high and extreme or crash volatility regimes) in the US REITs market. We document that the structure of regimes is as follows: from low to high to crash volatility. The above finding clearly supports the common belief the markets are in high volatility regime before and after a crash. Investors should be aware of this behavior that turbulence periods might be followed by crashes.

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APPENDIX

Table 1. Descriptive statistics

	Mean	Median	S.D.	Min	Max
Panel A: Cross sectional absolute deviation ($CSAD_t$)					
All equity REITs (EQUITY)	0.5048	0.3957	0.3447	0.1907	3.1931
Industrial/office (IO)	0.5096	0.377	0.4098	0.113	4.521
Retail (R)	0.4862	0.3543	0.3998	0.1199	4.0926
Residential (RES)	0.4296	0.3312	0.3394	0.0979	4.8375
Health care (H)	0.3723	0.318	0.2143	0.0723	1.7883
Lodging/resorts (LR)	0.6704	0.5038	0.5576	0.1347	5.816
Diversified (D)	0.5433	0.4068	0.4778	0.0692	6.4681
Other (OTHER)	0.3923	0.3126	0.3082	0.0374	3.8621
Mortgage (M)	0.7556	0.5474	0.6541	0.1531	9.1716
Panel B: Return (%) (R_t)					
All equity REITs (EQUITY)	0.0013	0.0336	0.9445	-9.2365	6.6822
Industrial/office (IO)	-0.0054	0.0339	1.0397	-11.2622	7.4545
Retail (R)	0.0006	0.041	1.0127	-9.3352	7.4555
Residential (RES)	0.0068	0.0285	0.8785	-7.628	6.1015
Health care (H)	0.0087	0.0367	0.889	-8.1673	6.3879
Lodging/resorts (LR)	-0.0068	0.0346	1.1553	-8.5883	8.2061
Diversified (D)	-0.0028	0.0311	0.8768	-9.6632	6.3257
Other (OTHER)	0.0156	0.0267	0.8457	-7.4408	5.3539
Mortgage (M)	-0.0385	0.0063	0.9294	-8.5241	6.4498

Note: Panels A and B report the descriptive statistics for daily market returns and cross sectional return dispersions across all listed equity REITs in each market as formulated in Equation (1), respectively. Sample period covers 1/2/2004-6/28/2013 at daily frequency with 2389 observations for each series. $CSAD_t$ is the cross-sectional absolute deviation of returns as a measure of return dispersion. R_t is the market log return in percent. REITs are classified into eight property sectors including Industrial/office (IO), Retail (R), Residential (RES), Health care (H), Lodging/resorts (LR), Diversified (D), Specialty, Timber and Self Storage (Other). We also consider Mortgage (M) REITs. All equity REITs (EQUITY) is the market portfolio of all REIT equities.

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Table 2. Estimates of the static model.

	α_0	α_1	α_2	RSS	log L	AIC	adj. R^2
All equity	0.2992***	0.3666***	0.0004	96.3560	445.1940	-0.3694	0.6602
	(0.0107)	(0.0344)	(0.0103)				
Industrial/office	0.2808***	0.3884***	-0.0078**	191.2241	-373.5115	0.3160	0.5229
	(0.0073)	(0.0186)	(0.0031)				
Retail	0.2574***	0.3827***	-0.0015	157.7126	-143.3655	0.1234	0.5865
	(0.0146)	(0.0446)	(0.0127)				
Residential	0.2525***	0.3134***	0.0138	120.9531	173.6206	-0.1420	0.5599
	(0.0095)	(0.0345)	(0.0121)				
Health care	0.2591***	0.2106***	-0.0029	62.8679	955.2619	-0.7964	0.4261
	(0.0055)	(0.0149)	(0.0042)				
Lodging/resorts	0.3745***	0.4371***	-0.0001	344.1511	-1075.4416	0.9037	0.5361
	(0.0121)	(0.0303)	(0.0071)				
Diversified	0.2763***	0.5591***	-0.0255	286.0666	-854.6306	0.7188	0.4747
	(0.0187)	(0.0649)	(0.0199)				
Other	0.2496***	0.2356***	0.0241*	123.0816	152.7827	-0.1246	0.4570
	(0.0106)	(0.0361)	(0.0135)				
Mortgage	0.4012***	0.6055***	0.0234	367.3325	-1153.3068	0.9689	0.6402
	(0.0189)	(0.0628)	(0.0216)				

Note: The table reports the estimates for $CSAD_t = \alpha_0 + \alpha_1 | R_{m,t} | + \alpha_2 R_{m,t}^2 + \varepsilon_t$. All estimations are done using the 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. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses are the HAC standard errors. A significant and negative α_2 estimate implies herding.

Table 3. Model selection criteria.

Panel A: log L	Static	MS(2)	MSH(2)	MS(3)	MSH(3)
All equity REITs	445.194	1305.420	2017.942	1727.391	2530.939
Industrial/office	-373.512	315.141	1086.552	641.999	1488.031
Retail	-143.366	640.287	1560.869	1086.685	1993.359
Residential	173.621	748.891	1416.076	1155.622	1748.357
Health care	955.262	1359.537	1584.887	1535.913	1758.202
Lodging/resorts	-1075.442	-361.643	327.113	-2.220	626.690
Diversified	-854.631	-141.590	623.536	219.561	882.778
Other	152.783	671.311	1190.545	1012.883	1488.706
Mortgage	-1153.307	-570.515	308.344	-0.739	573.956
Panel B: AIC					
All equity REITs	-0.369	-1.085	-1.681	-1.434	-2.104
Industrial/office	0.316	-0.256	-0.901	-0.524	-1.231
Retail	0.123	-0.528	-1.298	-0.897	-1.655
Residential	-0.142	-0.619	-1.177	-0.956	-1.450
Health care	-0.796	-1.131	-1.318	-1.272	-1.458
Lodging/resorts	0.904	0.310	-0.265	0.015	-0.510
Diversified	0.719	0.126	-0.514	-0.170	-0.726
Other	-0.125	-0.554	-0.988	-0.835	-1.232
Mortgage	0.969	0.485	-0.250	0.013	-0.467

Note: log *L* is the value of the log likelihood of the model under estimated parameter values. AIC is the Akaike Information Criterion. The static model is the herding regression model given in Equation (2). MS(k) is the Markov switching model given in Equation (3) with regime independent variance, $\varepsilon_t \sim iid(0,\sigma^2)$, and k regimes while MSH(k) is the Markov switching model with regime dependent or heteroscedastic variance, $\varepsilon_t \sim iid(0,\sigma^2_{S_t})$.

Table 4. Model selection tests.

	H_0: Static H_1: MS(2)	H_0: Static H_1: MSH(2)	H_0: Static H_1: MS(3)	H_0: Static H_1: MSH(3)
All equity REITs	1720.452*** (0.000) [0.000]	3145.496*** (0.000) [0.000]	2564.394*** (0.000) [0.000]	4171.490*** (0.000) [0.000]
Industrial/office	1377.306*** (0.000) [0.000]	2920.128*** (0.000) [0.000]	2031.022*** (0.000) [0.000]	3723.086*** (0.000) [0.000]
Retail	1567.306*** (0.000) [0.000]	3408.470*** (0.000) [0.000]	2460.102*** (0.000) [0.000]	4273.450*** (0.000) [0.000]
Residential	1150.540*** (0.000) [0.000]	2484.910*** (0.000) [0.000]	1964.002*** (0.000) [0.000]	3149.472*** (0.000) [0.000]
Health care	808.550*** (0.000) [0.000]	1259.250*** (0.000) [0.000]	1161.302*** (0.000) [0.000]	1605.880*** (0.000) [0.000]
Lodging/resorts	1427.598*** (0.000) [0.000]	2805.110*** (0.000) [0.000]	2146.444*** (0.000) [0.000]	3404.264*** (0.000) [0.000]
Diversified	1426.082*** (0.000) [0.000]	2956.334*** (0.000) [0.000]	2148.384*** (0.000) [0.000]	3474.818*** (0.000) [0.000]
Other	1037.056*** (0.000) [0.000]	2075.524*** (0.000) [0.000]	1720.200*** (0.000) [0.000]	2671.846*** (0.000) [0.000]
Mortgage	1165.584*** (0.000) [0.000]	2923.302*** (0.000) [0.000]	2305.136*** (0.000) [0.000]	3454.526*** (0.000) [0.000]
	H_0: MS(2) H_1: MSH(2)	H_0: MS(2) H_1: MS(3)	H_0: MSH(2) H_1: MSH(3)	H_0: MS(3) H_1: MSH(3)
All equity REITs	1425.044*** (0.000) [0.000]	843.942*** (0.000) [0.000]	1025.994*** (0.000) [0.000]	1607.096*** (0.000) [0.000]
Industrial/office	1542.822*** (0.000) [0.000]	653.716*** (0.000) [0.000]	802.958*** (0.000) [0.000]	1692.064*** (0.000) [0.000]
Retail	1841.164*** (0.000) [0.000]	892.796*** (0.000) [0.000]	864.980*** (0.000) [0.000]	1813.348*** (0.000) [0.000]
Residential	1334.370*** (0.000) [0.000]	813.462*** (0.000) [0.000]	664.562*** (0.000) [0.000]	1185.470*** (0.000) [0.000]
Health care	450.700*** (0.000) [0.000]	352.752*** (0.000) [0.000]	346.630*** (0.000) [0.000]	444.578*** (0.000) [0.000]
Lodging/resorts	1377.512*** (0.000) [0.000]	718.846*** (0.000) [0.000]	599.154*** (0.000) [0.000]	1257.820*** (0.000) [0.000]
Diversified	1530.252*** (0.000) [0.000]	722.302*** (0.000) [0.000]	518.484*** (0.000) [0.000]	1326.434*** (0.000) [0.000]
Other	1038.468*** (0.000) [0.000]	683.144*** (0.000) [0.000]	596.322*** (0.000) [0.000]	951.646*** (0.000) [0.000]
Mortgage	1757.718*** (0.000) [0.000]	1139.552*** (0.000) [0.000]	531.224*** (0.000) [0.000]	1149.390*** (0.000) [0.000]

Note: The Static model is the herding regression model given in Equation (2). MS(k) is the Markov switching model given in Equation (3) with a regime independent variance, $\varepsilon_t \sim iid(0,\sigma^2)$, and k regimes (0, 1 and 2) while MSH(k) is the Markov switching model with a regime dependent or heteroscedastic variance, $\varepsilon_t \sim iid(0,\sigma^2_{S_t})$. H_0 specifies the model under the null hypothesis that is tested against the alternative model under H_1. Test statistics are computed as the likelihood ratio (LR) test. The LR test is nonstandard since there are unidentified parameters under the null. The χ^2 p-values with degrees of freedom equal to number of restrictions plus the parameters unidentified under the null are given in parentheses and p-values of the Davies (1987) test are given in square brackets. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Estimates for the herding models under regime switching.

Parameter	All equity REITs	Industrial/office	Retail	Residential	Health care
$\alpha_{0,0}$	0.2940***	0.2466***	0.2841***	0.2259***	0.2196***
	(0.0031)	(0.0037)	(0.0048)	(0.0069)	(0.0059)
$\alpha_{0,1}$	0.1251***	0.3989***	0.6577***	0.3035***	0.2823***
	(0.0155)	(0.0114)	(0.0196)	(0.0162)	(0.0088)
$\alpha_{0,2}$	0.0516***	0.6569***	1.3650***	0.5656***	0.4646***
	(0.0141)	(0.0450)	(0.0359)	(0.0795)	(0.0392)
$\alpha_{1,0}$	0.4395***	0.1436***	0.1651***	0.0703**	0.0877***
	(0.0083)	(0.0143)	(0.0110)	(0.0298)	(0.0083)
$\alpha_{1,1}$	0.1692***	0.1096***	0.1460***	0.2369***	0.2064***
	(0.0180)	(0.0227)	(0.0203)	(0.0332)	(0.0160)
$\alpha_{1,2}$	0.0071	0.3404***	0.4923***	0.3066***	0.4014***
	(0.0071)	(0.0337)	(0.0297)	(0.0575)	(0.0767)
$\alpha_{2,0}$	0.5054***	0.0138	0.0204***	0.0038	0.0083***
	(0.0635)	(0.0116)	(0.0029)	(0.0090)	(0.0016)
$\alpha_{2,1}$	0.4153***	0.0140	0.0348***	0.0022	0.0017
	(0.0513)	(0.0086)	(0.0039)	(0.0087)	(0.0037)
$\alpha_{2,2}$	-0.0154*	-0.0100**	-0.0412***	-0.0346***	-0.0432*
	(0.0083)	(0.0046)	(0.0038)	(0.0010)	(0.024)
σ_0^2	0.0468***	0.0540***	0.0635***	0.0573***	0.0646***
	(0.0012)	(0.0029)	(0.0022)	(0.0045)	(0.0011)
σ_1^2	0.0930***	0.1097***	0.1311***	0.0947***	0.1016***
	(0.0031)	(0.0052)	(0.0064)	(0.0047)	(0.0021)
σ_2^2	0.4710***	0.4678***	0.4913***	0.3918***	0.2323***
	(0.0328)	(0.0315)	(0.0341)	(0.0502)	(0.0092)
p_{00}	0.9602	0.9375	0.9768	0.9172	0.9408
p_{01}	0.0643	0.0530	0.0548	0.0624	0.0370
p_{02}	0.0054	0.0416	0.0000	0.0000	0.0000
p_{10}	0.0389	0.0424	0.0232	0.0828	0.0581
p_{11}	0.9294	0.9224	0.9314	0.9162	0.9318
p_{12}	0.0210	0.0507	0.0374	0.0677	0.1312
p_{20}	0.0009	0.0201	0.0000	0.0000	0.0011
p_{21}	0.0063	0.0247	0.0138	0.0214	0.0312
p_{22}	0.9735	0.9077	0.9626	0.9323	0.8688
n_0	1353 [56.63%]	1043 [43.66%]	1532 [64.13%]	866 [36.25%]	778 [32.57%]
n_1	801 [33.53%]	886 [37.09%]	623 [26.08%]	1166 [48.81%]	1323 [55.38%]
n_2	235 [9.84%]	460 [19.25%]	234 [9.79%]	357 [14.94%]	288 [12.06%]
τ_0	28.79	18.96	51.07	15.75	24.31
τ_1	15.71	16.11	17.31	14.95	20.67
τ_2	39.17	11.79	33.43	16.23	9.29
n	2389	2389	2389	2389	2389
log L	2530.939	1488.031	1993.359	1748.357	1758.202
AIC	-2.104	-1.231	-1.655	-1.45	-1.458
LR	4171.490	3723.086	4273.450	3149.472	1605.880
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Davies Test	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Note: This table presents the estimates of the three regime MSH model given in Equation (3). Robust standard errors are reported in parentheses, which are obtained using the sandwich estimator of Huber (1967) and White (1982) based on the outer product of gradients and the second derivative matrix. n is the total number of observations, n_k is the number of observations in regime k with percentage of observation relative to the total number of observations given in the square brackets, τ_k is the duration of regime k, and LR test is the linearity test. The LR test is nonstandard since there are unidentified parameters under the null. The χ^2 p-values with degrees of freedom equal to the number of parameters unidentified are given in parentheses and the p-values of Davies (1987) test are given in square brackets. The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

(continued on the next page)

Table 5. (continued).

Parameter	Lodging/resorts	Diversified	Other	Mortgage
$\alpha_{0,0}$	0.3767***	0.2906***	0.3878***	0.3638***
	(0.0069)	(0.0053)	(0.0169)	(0.0060)
$\alpha_{0,1}$	1.1623***	0.4630***	0.2548***	0.4859***
	(0.0512)	(0.0236)	(0.0058)	(0.0180)
$\alpha_{0,2}$	2.2179***	1.1009***	0.9708***	1.0554***
	(0.0742)	(0.1253)	(0.0427)	(0.1148)
$\alpha_{1,0}$	0.3025***	0.2137***	0.2291***	0.2380***
	(0.0130)	(0.0205)	(0.0217)	(0.0143)
$\alpha_{1,1}$	0.3779***	0.2931***	0.0798***	0.5505***
	(0.0330)	(0.0406)	(0.0150)	(0.0251)
$\alpha_{1,2}$	0.7394***	0.5138***	0.5809***	0.7692***
	(0.0566)	(0.0931)	(0.0491)	(0.1260)
$\alpha_{2,0}$	-0.0034	0.0021	0.0126**	0.0652***
	(0.0030)	(0.0096)	(0.0055)	(0.0030)
$\alpha_{2,1}$	-0.0085*	-0.0012	0.0100*	0.0429***
	(0.0047)	(0.0124)	(0.0058)	(0.0048)
$\alpha_{2,2}$	-0.0509***	-0.0394***	-0.0456***	-0.0337***
	(0.0079)	(0.0110)	(0.0078)	(0.0120)
σ_0^2	0.1114***	0.0991***	0.0867***	0.1001***
	(0.0088)	(0.0037)	(0.0044)	(0.0017)
σ_1^2	0.2231***	0.1998***	0.1098***	0.2205***
	(0.0426)	(0.0166)	(0.0051)	(0.0067)
σ_2^2	0.7624***	0.8134***	0.4071***	0.8047***
	(0.0663)	(0.0994)	(0.0433)	(0.2200)
p_{00}	0.9729	0.9489	0.9746	0.9753
p_{01}	0.0504	0.1163	0.0247	0.0581
p_{02}	0.0000	0.0000	0.0000	0.0000
p_{10}	0.0271	0.0511	0.0246	0.0247
p_{11}	0.9342	0.8319	0.9523	0.9085
p_{12}	0.0508	0.2002	0.0892	0.0762
p_{20}	0.0001	0.0000	0.0008	0.0000
p_{21}	0.0154	0.0517	0.0229	0.0333
p_{22}	0.9492	0.7998	0.9108	0.9238
n_0	1407 [58.89%]	1587 [66.43%]	1084 [45.37%]	1491 [62.41%]
n_1	755 [31.60%]	637 [26.66%]	1049 [43.91%]	627 [26.25%]
n_2	227 [9.50%]	165 [6.91%]	256 [10.72%]	271 [11.34%]
τ_0	43.97	24.8	38.71	45.18
τ_1	17.56	6.71	20.17	12.06
τ_2	20.64	5.32	9.85	13.55
n	2389	2389	2389	2389
log L	626.69	882.778	1488.706	573.956
AIC	-0.51	-0.726	-1.232	-0.467
LR	3404.264	3474.818	2671.846	3454.526
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Davies Test	[0.000]***	[0.000]***	[0.000***	[0.000]***

Figure 1. Return and smoothed probability of 3-Regime nonlinear MS model for all equity REITs.

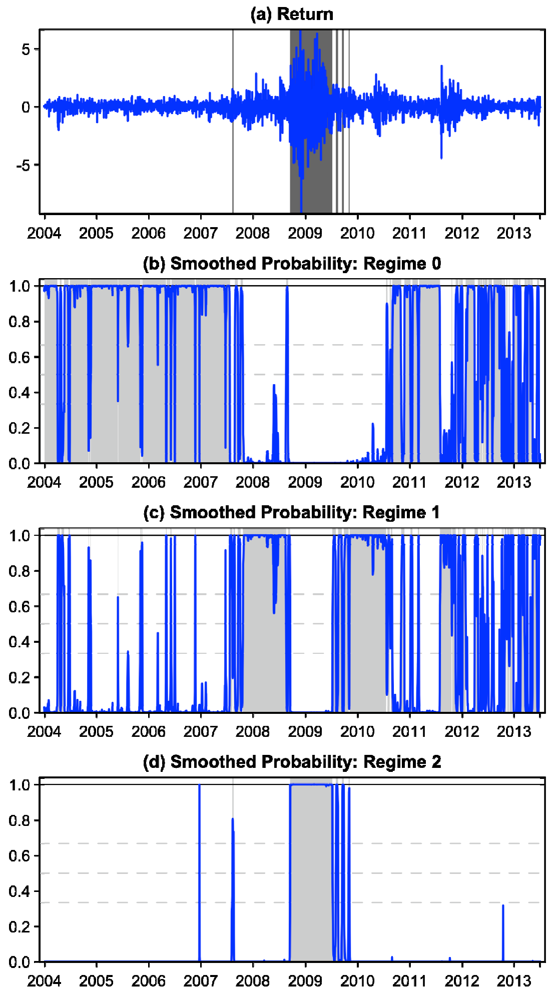
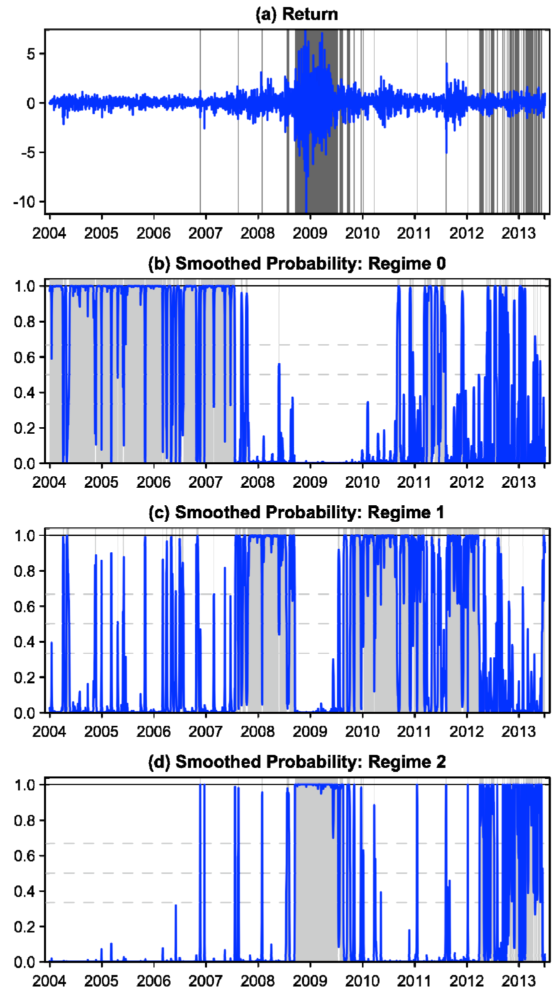
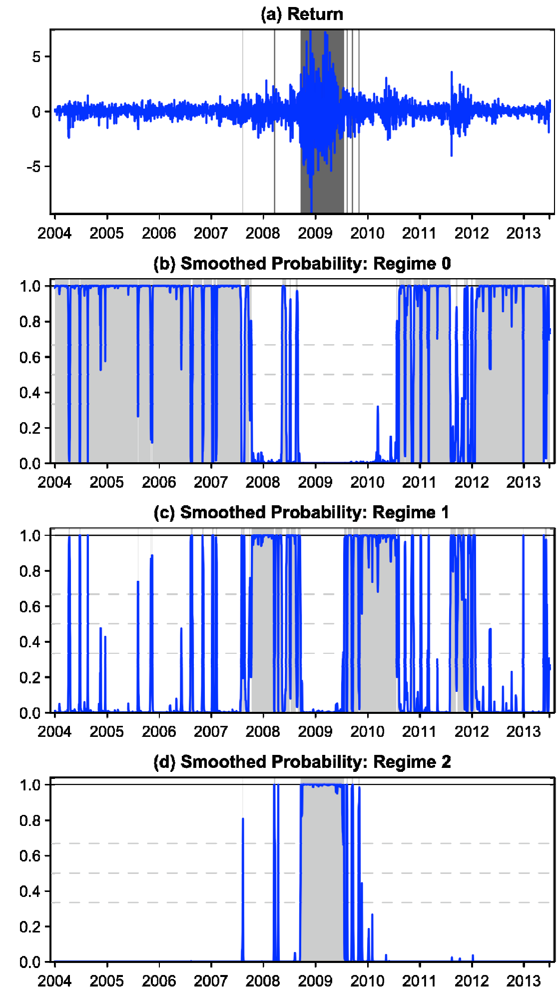


Figure 2. Return and smoothed probability of 3-Regime nonlinear MS model for industrial/office sector REITs.



Note: See note to Figure 1.

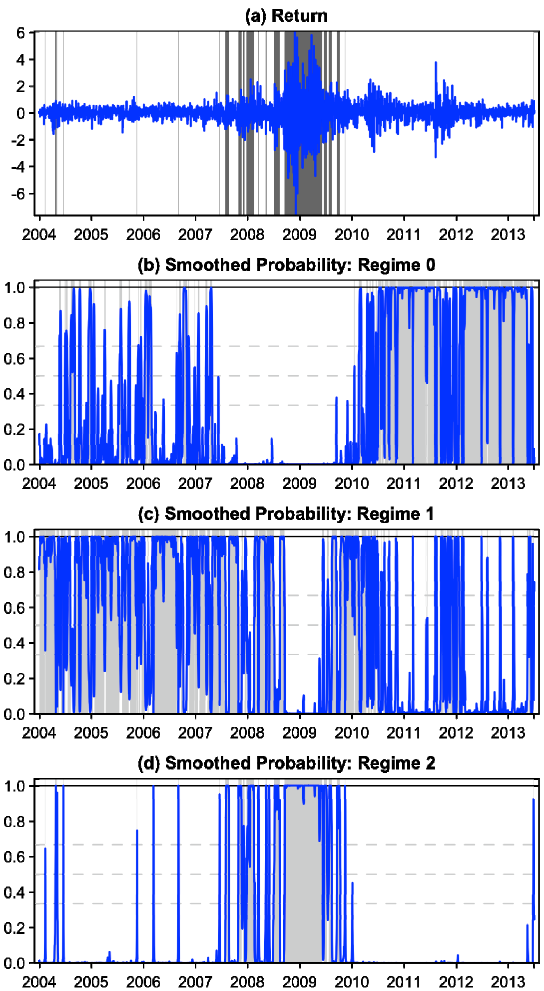
Figure 3. Return and smoothed probability of 3-Regime nonlinear MS model for retail sector REITs.



Note: See note to Figure 1.

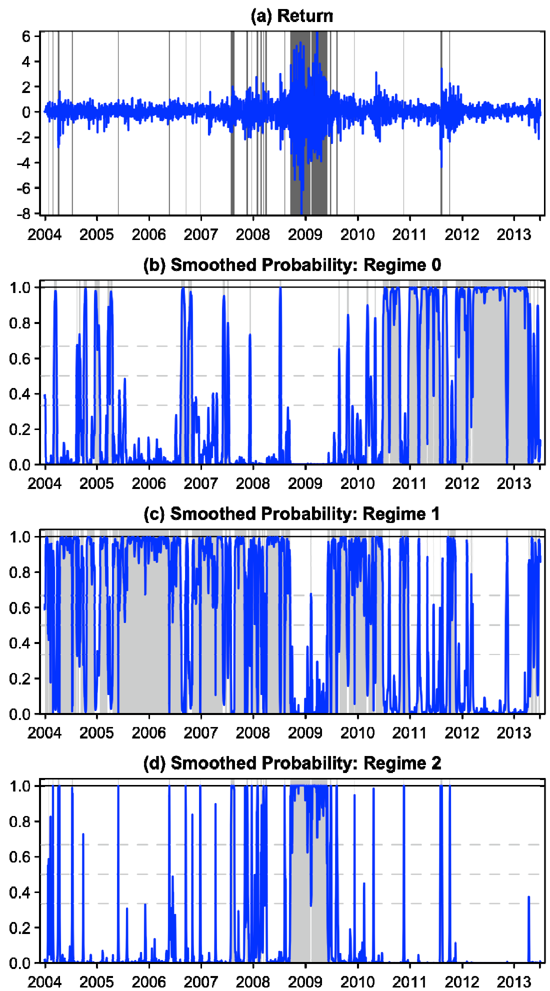
Note: Figure (a) plots the sectoral market return. The shaded regions in Figure (a) correspond to regimes where herding is supported with negative coefficients on squared returns in Equation (3). Figures (b)-(d) plot the smoothed regime probabilities for the 3-regime nonlinear MS model in Equation (3). The shaded regions in Figures (b)-(d) correspond to the maximum smoothed probability among the three smoothed probabilities. Regime 0 is the low volatility, Regime 1 is the high volatility and Regime 2 is the crash or extreme volatility.

Figure 4. Return and smoothed probability of 3-Regime nonlinear MS model for residential sector REITs.



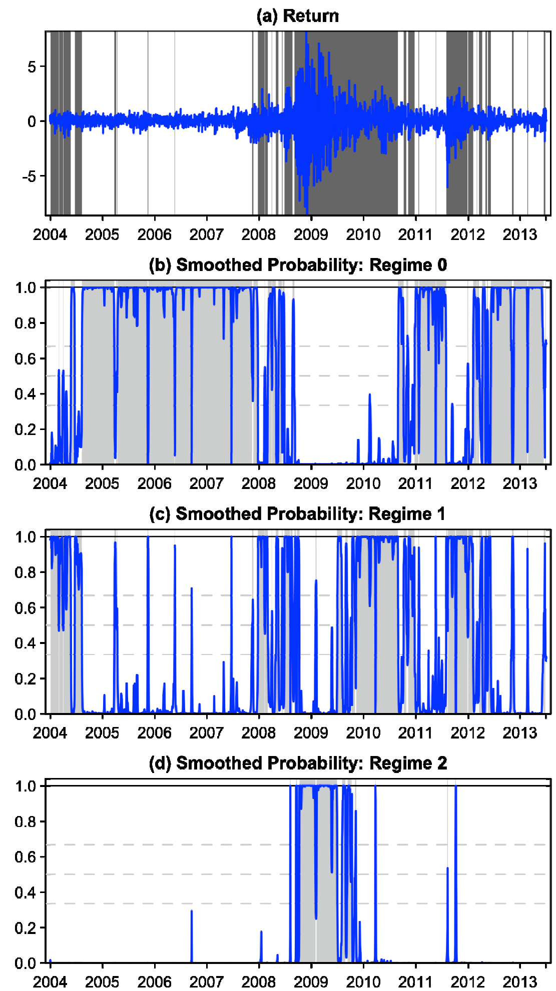
Note: See note to Figure 1.

Figure 5. Return and smoothed probability of 3-Regime nonlinear MS model for health care sector REITs.



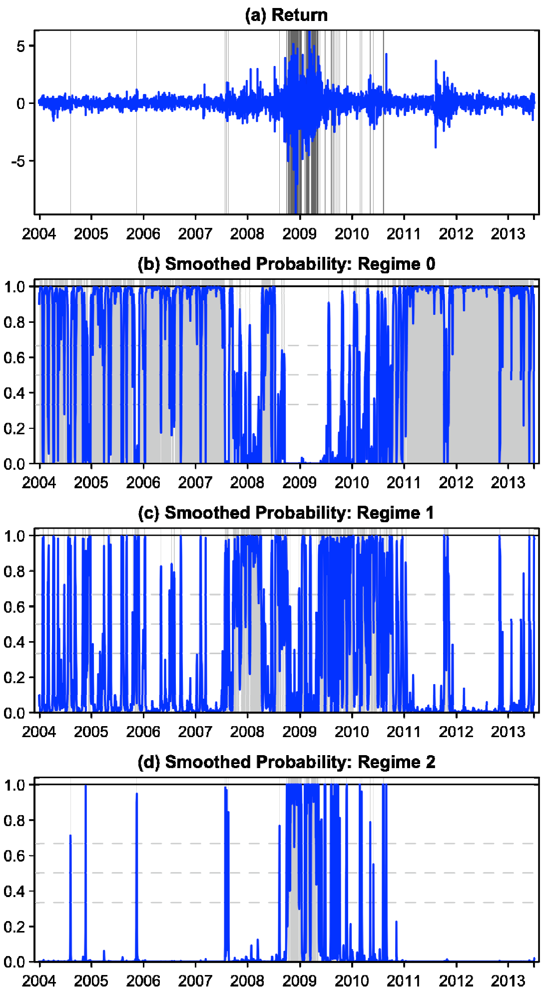
Note: See note to Figure 1.

Figure 6. Return and smoothed probability of 3-Regime nonlinear MS model for lodging/resorts sector REITs.



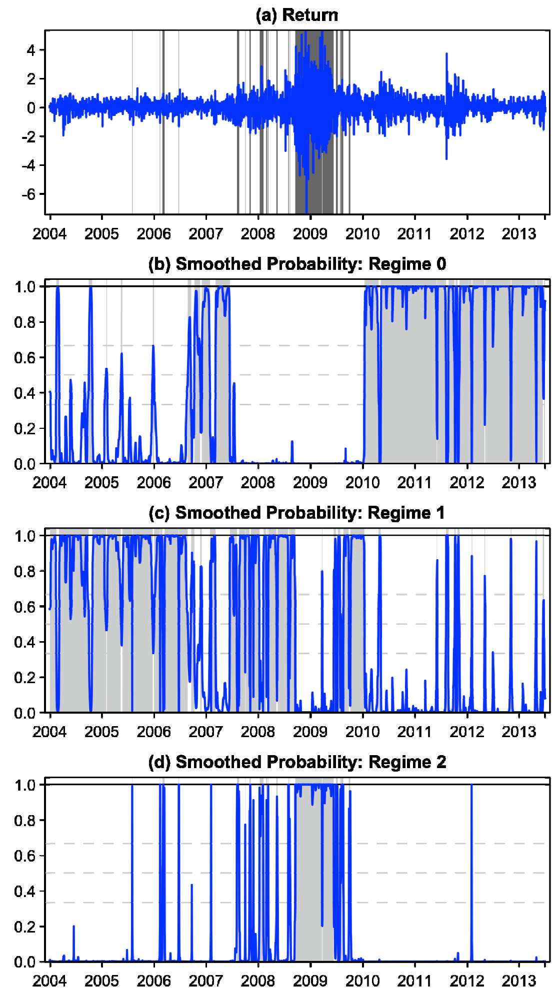
Note: See note to Figure 1.

Figure 7. Return and smoothed probability of 3-Regime nonlinear MS model for diversified REITs.



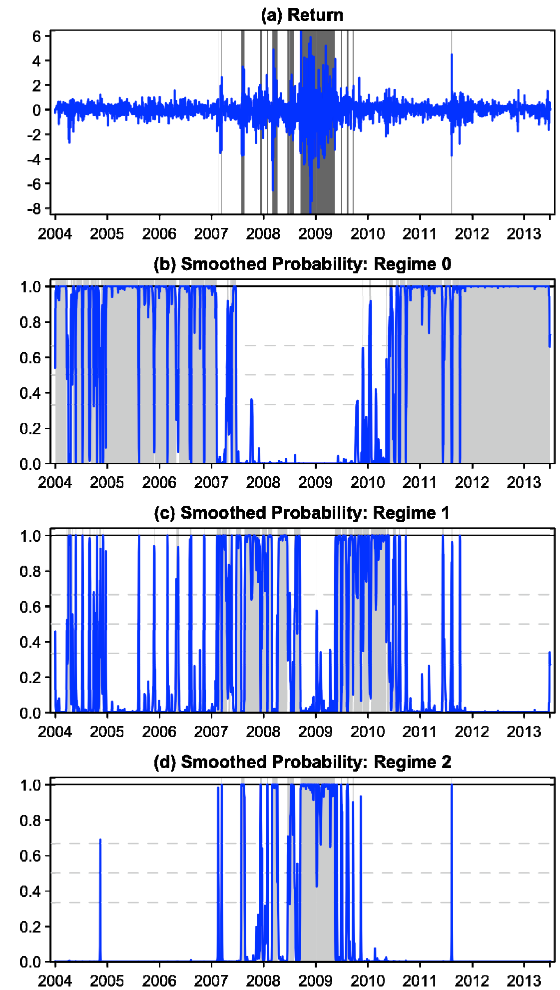
Note: See note to Figure 1.

Figure 8. Return and smoothed probability of 3-Regime nonlinear MS model for other sector REITs.



Note: See note to Figure 1.

Figure 9. Return and smoothed probability of 3-Regime nonlinear MS model for mortgage sector REITs.



Note: See note to Figure 1.