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Economic Policy Uncertainty and Herding Behavior: Evidence from the South African Housing Market**

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Abstract

This paper examines the link between economic policy uncertainty and herding behaviour in financial markets with an application to the South African housing market. Building on the evidence in the literature that herding behaviour driven by human emotions is not only limited to financial markets, but is also present in real estate investments, we examine the presence of herding in this emerging market via static and dynamic herding tests. While the static model fails to detect herding in the South African housing market, a dynamic model based on a two-regime Markov switching specification shows evidence of herding during the high volatility regime only, consistent with the notion that herd behaviour is primarily driven by increased market uncertainty. Extending our analysis via quantile regressions, we further show that higher quantiles of policy uncertainty are associated with greater likelihood of being in the herding regime, thus establishing a link between policy uncertainty and herding behaviour. Overall, our findings suggest that policy uncertainty can serve as a driver of market inefficiencies, which in our case, is associated by the presence of herding.

Keywords: Herding, Housing Market, South Africa, Regime-Switching, Uncertainty.

JEL: C34, G11, G15.

1. Introduction

Investor behavior in financial markets, with a particular focus on herding, has been extensively studied over the last decade, particularly following the recent financial market crises and subsequent global volatility spillovers. While most published works document evidence of investor herding, particularly in emerging stock markets and more prevalently during periods of market stress (e.g. Balcilar *et al*., 2013; Babalos *et al*., 2013; Yao *et al*., 2014; Balcilar and Demirer, 2015), a research question is whether certain global proxies of market stress can explain the evolution of herding or anti-herding in stock markets.

If one can identify such global proxies of market stress that significantly influence investors' behavior in local markets, particularly in emerging markets, regulators in those countries can focus on those stress proxies in order to monitor market volatility and develop safety nets and circuit breakers. Clearly, this is an important consideration as enlarged understanding of the herding-risk proxy relationship may help prevent the destabilizing effects of investor herding as herd behavior plays a role in affecting market volatility and pricing inefficiencies (e.g., Bikhchandani and Sharma, 2000; Blasco *et al.*, 2012).

Contrary to traditional financial theory which asserts that investors always make rational decisions on their investment choices and that the market is informationally efficient, with asset prices incorporating all available information, thus making sure market prices do not deviate too far from their intrinsic values. However, many researchers have been skeptical to the rationality of investors' decisions, thus to the concept of market efficiency, especially after a number of stock and assets price bubbles, such as the Dot.com bubble and US housing bubble that led to notorious market crashes. Theses price bubbles were characterized by a sharp increase in their values that were largely unexplained by fundamentals.

Following Keynes's view on the psychological perspective in the decision making (1936), in order to explain the market anomalies which do not conform to traditional finance models that are based on Efficient Market Hypothesis, the field of behavioral finance has merged over the last two decades, focusing on investor psychology in financial decision making. According to the behavioral finance arguments, investors are not fully rational as they tend to be influenced by cognitive bias that might deviate asset prices from their fundamental values, thus leading to bubbles and subsequent crashes.

Shiller (1989) and Sherfin (2000) contend that the fluctuations in asset prices may not necessary follow the arrival of new fundamental information to the market, but rather by investors' collective behavior driven by their emotions. Henceforth, the role of human behavior in investors' decision has been incorporated in theoretical and empirical models and has proven to play an important role in the determination of financial assets' market values.

One behavioral bias that influences investment decisions identified by researchers is herding which is defined as a tendency of investors to mimic the actions of other investors for various reasons. The literature argues that investors' decision to herd may be driven by rational or irrational motives. For example, Bikhchanding et *al.* (1992) propose an informational cascades model to show that rational individuals may ignore their private information and base their decision on other investors' decisions. A similar argument is put forward by Banerjee (1992) using the sequential decision model, while Scharfstein and Stein (1990) argue that the managers concerned with their reputation will choose to ignore their private information and follow others.

Furthermore, the remuneration has been the other source of herding behaviour (Brennan, 1993). Later, Bikhchandani and Sharma (2001) distinguish between spurious and intentional herding behavior, with the former being the rational response of investors to the same fundamental information, while the latter is considered to be irrationally driven by human emotions. Regardless of whether herding behavior is based on rational or irrational motives, such behavior has been identified as one of the causes of price bubbles in a number of studies. From a market efficiency perspective, Shiller (2000) argues that even though the individual may be rational to follow the market consensus, the outcome of excessive herding in financial market can still lead to market inefficiency.

A number of studies in the literature have presented evidence to support the presence of herding. Bowe and Domula (2004) analyze the behavior of both foreign and domestic investors before, during and after the Asian financial crisis; and find a tendency of both types of investors to herd while foreign investors herd more at the beginning of the crisis. In an early study, Demirer and Kutan (2006) find no evidence of herding behavior using both firm-and sectoral level data from two Chinese stock markets whereas Chiang and Zeng (2010) documents evidence of herding in the Asian and advanced stock markets, with the exception of the US stock market. Similarly, Ouarda et *al*. (2013) document evidence of herding behavior in the developed European stock markets during the 2007-2008 financial crisis and the Asian crisis periods.

According to Bikhchandani and Sharma (2001) and Sias (2009), herding behavior is more likely to happen in the same industry or sector as the investors tend to receive the same information and are more likely to make similar investment decisions. In an application to the property sector in a developing market, Sharma et *al*. (2015) find strong evidence of herding behaviour on both Shanghai and Shenzhen stock exchanges with more prevalent herding behaviour in the industrial and property sectors compared to other sectors. Given that the 2007/2008 U.S. crisis started as a housing market bubble, later leading to a financial crisis at a global scale, several researchers have directed their attention specifically to the cause of the price bubbles and the role of herding behaviour during financial crisis.

Analysing the role of herding behaviour in house prices of seven-European and three non-European OECD countries, Hott (2012) shows that part of the fluctuations in house prices is associated with herding behaviour. Similarly, Nneji et *al.* (2013) examine whether or not changes in rents predict price growth in times where intrinsic or rational bubbles exist.

By splitting the sample into two sub-periods, the first period (1960-1999) shows the existence of an intrinsic bubble, where buyers react to changes in the cost of renting, thus leading to overvaluation of real estate prices. However, the second period (2000-2011) shows no signs of intrinsic bubbles, but rather rational speculative bubbles caused by exogenous factors other than rent. This evidence suggests that the role of herding behavior in the housing market can best be examined by considering various market regimes.

Extending herding tests further into real estate markets, Vassilios et *al*. (2014) examine herding behaviour of U.S. listed Real Estate Investment Trusts (REITs) via a three-regime Markov switching model and show strong evidence of herding behaviour under the crash regime. They also observe a shift from negative herding behaviour during the low and high volatility regimes to positive herding behaviour under the crash regime for almost all REIT sectors. Zhou and Anderson (2013) provide further support for the presence of a market-wide herding behaviour in the U.S. REITs.

Using the quantile regressions, they find herding behaviour to be more prevalent in the higher quantile of the cross-sectional dispersion in REIT returns where herding is more likely to occur and turn stronger in declining markets than in rising markets. However, focusing on the housing market in 30 Chinese provinces and municipal cities and using quantile regressions, Lan (2014) finds herding behavior to be more prevalent in increasing markets than in decreasing markets.

These mixed results overall support the later finding by Ngene et *al*. (2017) that the degree of herding in the U.S. residential housing market varies across regimes, regions and conditional distributions. Finally, Akinsomi et *al.* (2018a) investigate the role of volatility and equity market uncertainty in determining the herding behavior in UK real estate investment trusts using both static and Markov Switching approaches. While the static herding model shows no existence of herding in the REIT markets, anti-herding behavior is observed in the higher volatility regime and herding behavior in the low volatility regime.

Despite the multitude of herding studies on the housing market primarily for developed countries, there are few studies for emerging markets. In the case of the South African housing market, Loewis et *al.* (2016) find anchoring and adjustment as heuristic-driven bias and show that herding behavior influences South African property fund managers' investment decisions using survey information.

Another recent study by Ababio and Mwamba (2017) examine herding behavior in Johannesburg Stock Exchange and find herding behavior to be prevalent during normal market states in the financial and real estate sectors. Akinsomi et al., (2017, 2018b) also provide evidence of herding in South African and Turkish REITs, based on regime-switching models. Our study contributes to the empirical evidence of herding behaviour in emerging markets by focusing on the South African housing market and examining the role of economic policy uncertainty as a possible driver.[1]

Our interest in the South African housing market is motivated by the fact that residential investments are mainly driven by private business enterprises and have shown an exponential increase since 2000's despite a market downturn during the financial crisis. The real returns on the South African property asset class have outperformed cash, equities, gold and bonds over the last 10 and 20 years respectively according to long term perspectives (2018) published by Old Mutual.

However, according to the IMF World Economic Outlook (2003), even though housing price bubble leading to busts are less frequent than stock market bubbles, they tend to generate more output losses compared to stock price crashes. This may be caused by the fact that the property assets are highly illiquid and are primarily financed using borrowed funds. Hence, a proper investigation of what drives the housing price in South Africa is very important in order to minimize the risk of financial disasters that may be caused by herding behaviour of investors.

[1] Using rolling estimation of the herding model as an alternative approach to regime-switching, Cakan et al., (2019) show that speculation in the oil market could serve as a driver of herding in oil exporting and importing emerging markets.

While our results for the static model show no evidence of herding behavior in the South African housing market, dynamic specification based on a two-regime Markov Switching model detec herding during the high volatility regime only. Extending our analysis via quantile regressions, we further show that higher quantiles of policy uncertainty are associated with greater likelihood of being in the herding regime, thus establishing a link between policy uncertainty and herding behaviour.

Overall, our findings suggest that policy uncertainty can serve as a driver of market inefficiencies, which in our case, is associated by the presence of herding. The remainder of paper is organized as follows. Section 2 describes the data and the methodology. Section 3 discusses the empirical results and Section 4 concludes.

2. Data and Methodology

2.1 Data

We use quarterly data for housing price indexes covering 9 regions (Eastern Cape, Free State, Gauteng, KwaZulu-Natal, Limpopo, Mpumalanga, North-West, Northern Cape, Western Cape) over the period from 1977Q4 to 2016Q3, yielding a total of 156 quarterly observations. The dataset covers three different size of houses: small ($80m^2$-$140\ m^2$), medium ($141\ m^2$-$220\ m^2$) and large ($221\ m^2$-$400\ m^2$).[2] The data is sourced from the Allied Bank of South Africa (ABSA) housing price survey, with ABSA being one of the leading private banks in South Africa.

[2] According to ABSA, the housing prices are categorized in three segments based on their value: luxury (ZAR 3.5 million-ZAR 12.8 million), middle (ZAR 480000-ZAR 3.5 million) and affordable (below ZAR 480000 and area between $40m^2$-$79m^2$). The middle segment is the one that is further divided into three more according to their size. This is the segment that we use, since provincial data is not available for the luxury and affordable segments. To compile these indices, ABSA follows a specific process: Firstly, data are extracted from applications for mortgage finance that were approved by the bank. Then these data including purchase prices, building and land area and building and land value among others are generated and filtered for the different size categories. Cut–off prices for affordable, middle and luxury segments are determined once a year based on various trends such as the CPI inflation and growth in housing prices. These series are then seasonally adjusted and smoothed and the average house price data series are compiled for each segment. For the sub-segments (small, medium and large) the weighted average is lastly combined based on the sample sizes of each of the segments.

2.2 Testing methodology

We use the testing methodology of Christie and Huang (1995), later improved by Chang et al.(2000) to detect herding behavior. The benchmark model is developed from the CAPM specification of returns and uses the deviations from the CAPM to make inferences on the presence of herding. The test focuses on the cross-sectional absolute deviation of returns (CSAD) expressed as:

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

where *N* is the number of regions in the same size of housing prices, $\boldsymbol{R}_{i,t}$ is the observed return on the equal-weighted portfolio of small, medium and large houses of a region *i* for quarter *t* and $\boldsymbol{R}_{m,t}$ is the return on the equally-weighted market portfolio based on the aggregate house prices for the whole of South Africa for quarter *t*.

Using the CAPM specification, one can show that expected CSAD should, in theory, have a non-negative relation with the expect market return, implied by a non-negative first derivative with respect to expected market return, while the second derivative with respect to the market return is zero. This implies that greater cross-sectional dispersion in asset returns should, in theory, be expected for larger market movements and the relationship between market return and cross-sectional return dispersion should be linear.

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

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

where $\varepsilon_t \sim iid(0,\sigma^2)$, and a significant and negative estimate for α_2 is used as support for the presence of herding.

As the herding test in Equation 2 is based on the coefficient of the non-linear term, we focus on the herding coefficient, α_2, as a proxy for the level of herding in the housing market so that increasingly negative values for the herding coefficient indicate higher degree of herding whereas positive and significant values indicate anti-herding. However, considering that the constant parameter model over the sample period proposed by Chang *et al*. (2000) may lead to biased results in case herding behavior depends on economic or financial conditions, alternatively we consider a regime dependent herding model via a two-regime Markov switching model as:

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

where S_t is a discrete unobservable regime variable taking the values of 1, 2. The transition between the regime is governed by the first order Markov process, which means that S_t depend only on the previous regime S_{t-1} as denoted below:

$$p_{ij} = pr\left(S_t = i / S_{t-1} = j\right), i, j \in \{1, 2\}.$$

The value p_{ij} is known as the transition probability of moving to state i from state j and is assumed to be independent of time. Hence, the probability of switching can be represented in a 2 × 2 matrix:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}$$

The transition probabilities must satisfy the condition that $\sum_i p_{ij} = 1$ for all j.

The original Markov switching model pioneered by Hamilton (1989) and its variants have been applied in numerous financial studies (Guidolin and Timmermann; 2006; Schwert, 1989 and Schaller and Norden, 1997; among others) and more specifically to investigate the herding behavior in the real estate market (e.g. Lan, 2014; Vassilios et *al.*, 2014 and Akinsomi et *al.*, 2016; among others).

The Markov switching approach is shown to produce better results as it captures nonlinearities and asymmetries that are likely present in the housing market as the appetite for investment in real estate market as well as the asset performance tend move with the business cycles, recessionary and expansionary periods is characterized by bull and bearish market.

3. Empirical Results

As mentioned earlier, based on the Capital Asset Pricing Model (CAPM) specification, the herding model shown in Equation (2) indicates herding by a negative relationship between the cross-sectional dispersions in returns (CSAD) and squared marked return, implied by a negative and significant α_2 estimate. The results for the static model presented in Table 1 indicate the absence of herding over the entire sample, implied by positive and statistically significant α_2 estimate.

The positive estimate in fact implies anti-herding in which investors deviate from market consensus rather than go with the consensus. We also observe in Table 1 that the coefficient α_1 of the static model is negative and statistically insignificant, contradicting the CAPM expectation for the cross-sectional return dispersion to be positively related to the absolute market return.

As noted earlier, the static model in Eq. (2) can lead to misleading conclusions regarding herd behaviour as parameters are assumed to be constant over time. To verify this line of reasoning, the powerful tests of Bai and Perron (2003) are applied to Eq. (2), to detect 1 to *M* structural breaks, allowing for heterogeneous error distributions across the breaks. Based on these tests, five breaks are detected at: 1983Q3, 1989Q4, 1995Q3, 2001Q2, and 2009Q4, as shown in Table A1 in the Appendix.

In addition, the nonlinearity test of Brock et al., (1996), the BDS test, is applied to the residuals of the static model in Eq. (2). Results obtained, and reported in Table A2 in the Appendix show strong evidence (at highest level of significance across all possible dimensions) of nonlinearity. Together, the structural breaks and nonlinearities confirm the unreliability of the static model in Eq. (2) and its results. Hence, we now turn our attention to the nonlinear regime-switching model.

The results for two-regime Markov switching model are presented in the Table 2. The lower volatility regime, “Regime 1” (i.e., where the conditional mean value of the *CSAD* is lower), clearly shows the absence of herding behavior since the coefficient of squared market return is statistically insignificant. However, herding behavior is observed in the high volatility regime, “Regime 2”, as the coefficient of squared market return displays a negative sign and it is statistically significant at 5% level.

The negative and significant coefficient of squared market return during the high volatility regime indicates the presence of herding behavior in the housing market, implying that investors tend to herd during periods of large price fluctuations. Moreover, the coefficient of absolute return in the high volatility regime (Regime 2) is positive and statistically significant, consistent with the CAPM expectation.

Examining the estimated transition probabilities in Table 3, we further observe a 99.34% probability of remaining in the low volatility regime and 0.65% probability of switching to the high volatility regime, while there is a 97.68 % probability of remaining in the high volatility regime when the market is in the high volatility regime with only 2.3 % probability to switch to the low volatility regime. This shows that there are only few switches that can be expected between the herding and no-herding regimes.

Furthermore, the regime duration which is assumed to be constant, indicates that the low volatility regime is more persistent, lasting for 154 quarters compared to the high volatility regime which has an average duration of 43 quarters. Given that the high volatility regime is relatively short lived, we might expect herding behavior to occur during a short period, although its impact can be detriment to the financial system and overall economy.

The results overall show the importance of considering dynamic specifications in herding tests. These observations are further explained graphically with the filtered probabilities for both regimes as well as the CSAD plot, presented in Figure 1. As can be seen in the plots, the two-regime Markov switching model successfully identifies the turning points observed in the CSAD time series. Moreover, the filtered probability for the two regimes are in line with expected duration results, with the low volatility regime lasting longer than the high volatility regime.

In order to provide further insight to the possible drivers of herding and following recent studies including Ngene et al. (2017) and Akinsomi et al. (2018a), we next explore the possible role of economic uncertainty as a driver of herding. These studies suggest that since economic uncertainty leads other macroeconomic and financial variables, it captures fundamental sources of uncertainty.

Given this, we relate the Regime 2 probability with a measure of economic uncertainty using the metric developed by Hlatshwayo and Saxegaard (2016) on the economic policy uncertainty (EPU) for South Africa. EPU is a news-based index of uncertainty based on key search terms including economy, policy, uncertainty and South Africa.[3]

In the second part of our empirical analysis, we use a quantile regression approach in order to capture the effect of EPU on the entire conditional distribution of the probability of herding and not just its conditional mean.[4] Quantile regression was introduced in the seminal paper by Koenker and Bassett (1978). It is a generalization of median regression to other quantiles. The coefficients of the τ^{th} conditional quantile distribution are estimated as:

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[3] The index is available for download from: https://sites.google.com/site/sandile1984hlatshwayo/research?authuser=0.

[4] The OLS regression yields insignificant impact of EPU on the herding probability even at the 10% level of significance. Complete details of these results are available upon request from the authors.

$$\widehat{\beta}\,(\tau) = \arg\min \sum_{t=1}^{\tau} \left(\tau - 1_{\{y_t < x_t' \beta(\tau)\}}\right) |\, y_t - x_t' \ \beta(\tau)| \ ,$$

where the quantile regression coefficient $\beta(\tau)$ determines the connection between the vector of independent variables (in our case EPU) and the τ^{th} conditional quantile of the dependent variable (in our case the probability of herding under Regime 2), with $1_{\{y_t\iota < x_t' \beta(\tau)\}}$ being the usual indicator function.

The *t*-statistics of the quantile estimates corresponding to EPU are reported in Figure 2. We observe that that EPU significantly increases the probability of being in the herding regime at (conditionally) higher quantiles, i.e. over the range of 0.55 to 0.95 (though intermittently).[5] In general, as in the recent existing literature, we also do find evidence that herding in South African housing market is increased in the wake of uncertainty, thus establishing a link between policy uncertainty and market conditions during which herding is more likely to occur.

4. Conclusion

This paper adds to the empirical evidence of herding behavior in financial markets by extending herding tests to the South African housing market. The South African housing market has experienced a significant boom in market size fueled by a rise in residential investments since 2000's. Beside the influence by economic fundamentals such as interest rates, inflation, population growth, rental prices, and growth in income that can stimulate growth in the housing market, non-fundamental determinants such as herding behavior have also been suggested in a number of studies as a possible cause for recurring price bubbles in this growing market. Hence, this paper examines the presence of herding behavior in the South African housing market and the possible role of economic policy uncertainty as potential driver.

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[5] Note the EPU data starts in 1985:Q1, and hence the quantile estimation starts from that date. The EPU index also has two sub-indices namely, economic uncertainty and policy uncertainty. These two indices also provided similar evidence as with the overall EPU. These indices start from 1990:Q1. Complete details of these results are available upon request from the authors.

While the static model shows no evidence of herding behavior in this market, a battery of tests including the Brock et al. (1996) and Bai and Perron (2003) tests for nonlinearity and structural breaks respectively, justify the use of a Markov Switching model to account for possible regimes in the time series. Unlike the static model, the regime-based tests indicate the presence of herding during the high volatility regime and no herding during the low volatility regime, further supporting the general consensus in the literature that herding is more likely during periods of high market uncertainty.

Further extending our study via quantile regressions, we next show that higher quantiles of economic policy uncertainty increase the probability to be in the herding regime, thus establishing a link between policy uncertainty and investor behavior. An important implication of our findings is that increased uncertainty regarding economic policies can not only deter investments and spending, but can also lead to market inefficiencies, which in our case is captured by investors' tendency to herd. To that end, policy makers should take into account the possible behavioral implications of their actions while taking decision on economic policies and be aware that uncertainty regarding economic policies can lead to not only increased volatility in the housing market, but also informational inefficiencies in the pricing of these assets.

This is certainly an important consideration given that herding behavior does not lead to favorable outcomes as painfully experienced during the US financial crisis that originated from the real estate market.

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Figure 1

Plots of cross-sectional return dispersion (CSAD) and regime probabilities

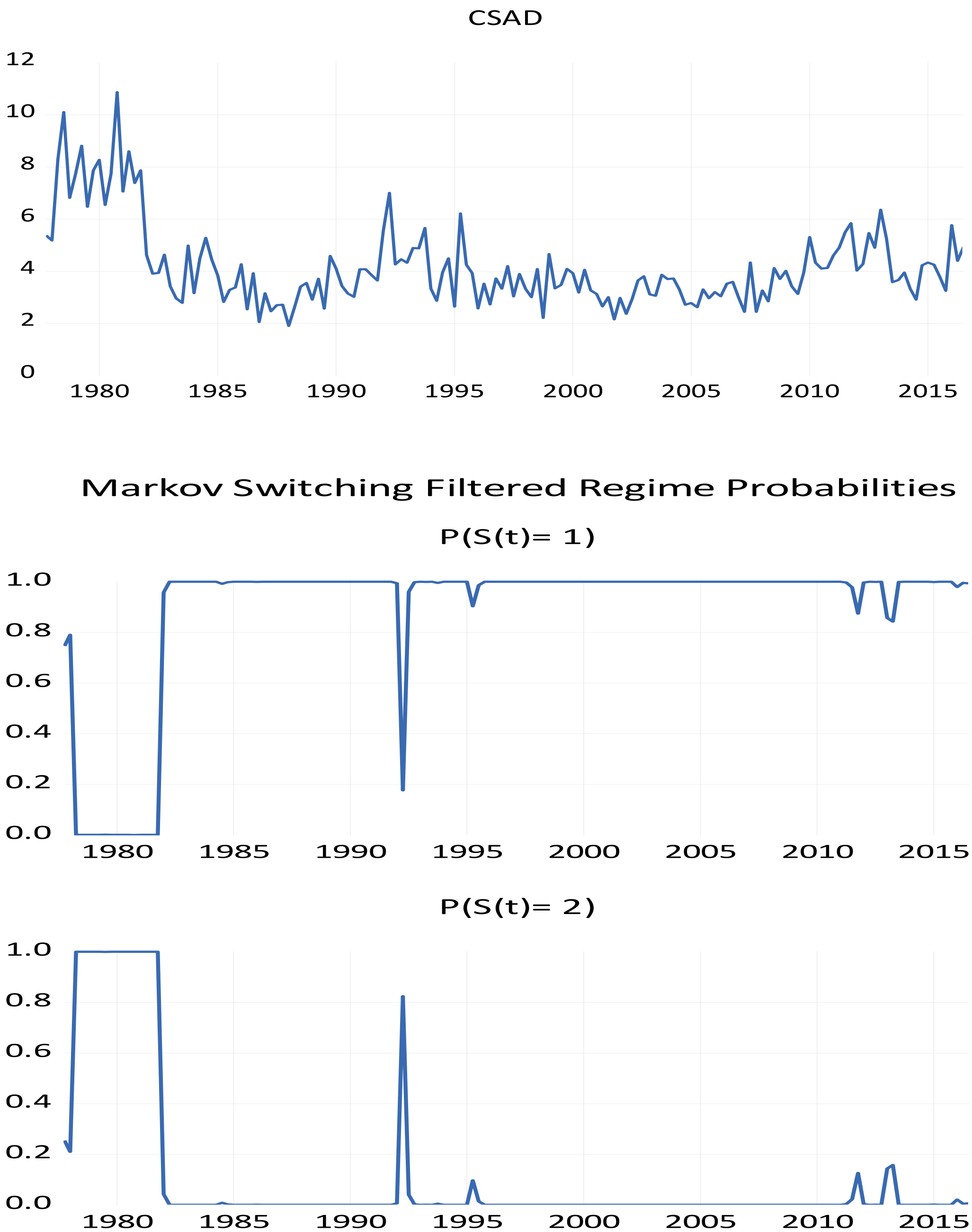
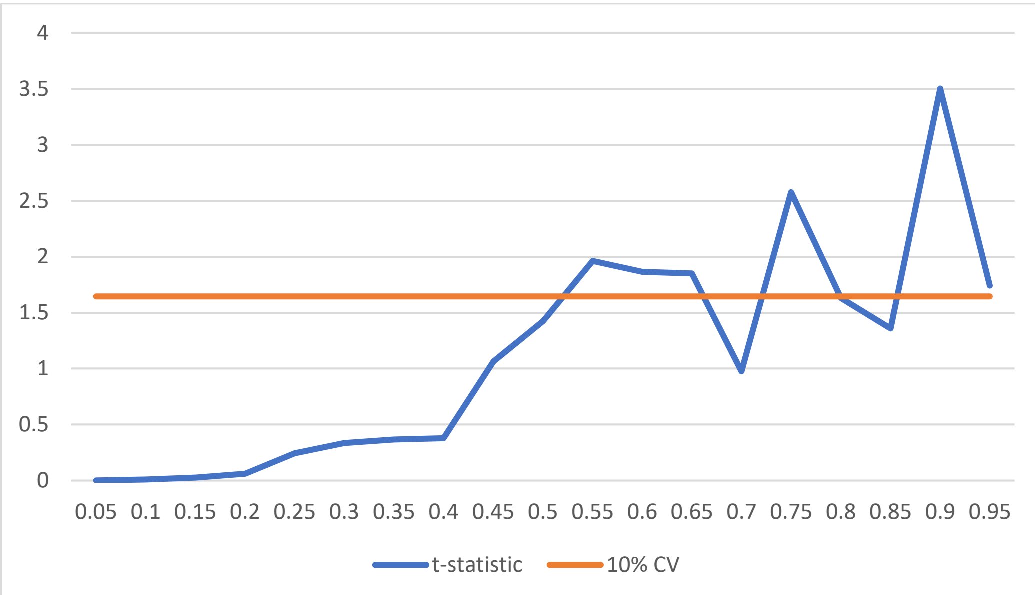


Figure 2

t-statistic of quantile process estimates



Note: 10% CV corresponds to a value of 1.645, with the horizontal axis reporting the quantiles.

Table 1

Estimates for the static model

α_0	α_1	α_2	RSS	Log$L$	AIC	adj.R^2
4.2514***	0.2450	0.5068**	1.4947	-287.0629	3.7188	0.0667

Note: The table reports the estimates for the static CSAD model in Equation (2). All estimations are done using the ordinary least squares (OLS). 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% and 5% levels, respectively. A significant and positive α_2 estimate implies anti-herding behavior.

Table 2

Two-regime Markov Switching results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
$\alpha_{1,1}$	-0.188461	0.128401	-1.467752	0.1422
$\alpha_{2,1}$	0.016272	0.017799	0.914215	0.3606
$\alpha_{0,1}$	4.059738	0.194338	20.89005***	0.0000
Regime 2				
$\alpha_{1,2}$	0.706246	0.293425	2.406906**	0.0161
$\alpha_{2,2}$	-0.053270	0.027068	-1.968031**	0.0491
$\alpha_{0,2}$	6.100910	0.652195	9.354422***	0.0000
Common				
$\log(\sigma)$	-0.044102	0.060472	-0.729291	0.4658
Transition Matrix Parameters				
p_{11}-c	5.027227	1.195202	4.206174	0.0000
p_{21}-c	-3.743184	1.866211	-2.005767	0.0449
Log$L$	-221.4607			
AIC	2.954625			

Note: The table reports the estimates for the two-regime, Markov Switching CSAD model. ***, ** represent significance at the 1% and 5% levels, respectively.

Table 3

Transition probabilities

$p(i, j) = P(s(t) = j \mid s(t\text{-}1) = i)$

		1	2
Whole sample	1	0.993487	0.006513
	2	0.023124	0.976876

Note: The table reports the estimated transition probabilities for the two-regime, Markov Switching CSAD model.

Appendix

Table A1

Bai and Perron (2003) multiple structural break test

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	1
WDmax determined breaks:	1

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	15.66452	46.99357	46.99357	13.98
2 *	12.47045	37.41135	43.62057	11.99
3 *	11.39983	34.19949	46.01625	10.39
4 *	9.017767	27.05330	41.79062	9.05
5 *	7.662427	22.98728	43.07804	7.46

UDMax statistic*	46.99357	UDMax critical value**	14.23
WDMax statistic*	46.99357	WDMax critical value**	15.59

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

Estimated break dates:
1: 1983Q3
2: 1983Q3, 2010Q1
3: 1983Q3, 2000Q4, 2009Q4
4: 1983Q3, 1989Q4, 1995Q3, 2009Q4
5: 1983Q3, 1989Q4, 1995Q3, 2001Q2, 2009Q4

Note: The break test is applied on Eq. (2), i.e. the benchmark herding model, and the test options involve 1 to *M* globally determined breaks, with a trimming of 15%, maximum allowed breaks of 5, and heterogeneous error distributions across breaks.

Table A2

Brock et al., (1996) BDS test

m	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.083453	0.007836	10.65044	0.0000
3	0.147159	0.012517	11.75667	0.0000
4	0.179025	0.014986	11.94631	0.0000
5	0.200900	0.015706	12.79164	0.0000
6	0.207672	0.015231	13.63500	0.0000

Note: The BDS *z*-statistic tests for the null of *i.i.d.* residuals. *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.