Empirical Research on Herding Effects: Case of Real Estate Markets

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This research investigates the existence of herding effects in the real estate market. Case-Shiller Index is used to demonstrate the relationship between herding and the markets. Following the approach in Christie and Huang (1995), we investigate the presence of herd behavior among individuals. Our research presents evidence that herding does not affect individual returns from the housing market. Instead, our findings support the prediction for individual return dispersion offered by the rational asset pricing model.

Keywords: herd behavior, real estate market, dispersion

INTRODUCTION

In the finance literature, the herding is defined as a form of imitation leading to an alignment of behavior (Shefrin, 2000; Welch, 2000; Hirshleifer and Teoh, 2003). Many scholars examine if the herding behavior or speculation creates an environment in which the bubble can thrive. They demonstrate the relationship between the herding effect and financial instruments. Blindly following such behavior leads investors to make similar decisions, entailing mispricing of financial securities (Shiller, 2003). Additionally, research has found herding behavior affecting the return on the Real Estate Investment Trusts (henceforth REITs). Zhou and Anderson (2013) examine the herding behavior in the U.S. REIT market. According to authors, a herding behavior is described as a person who suppresses his or her own beliefs and follows the actions of others. They conduct an empirical study detecting the existence of the herding effect. By focusing on REIT market-wide rather than group-wide herding, authors present evidence that investors show the herding behavior especially when the market is not stable.[1]

Among many, one that is directly related to the recent financial crisis is the real estate bubble. Even though the bubble in the US residential housing market affects more than half of the US, only a few empirical studies have attempted to establish a link between herding behavior and housing markets. Therefore, the purpose of this research is to shed light on the impact of herding on real estate markets. The prior study conducted by Christie and Huang (1995) suggests that individuals tend to guide their investment decisions on the collective actions of the market which is attributed to the change in the market return. Therefore, the herd behavior keeps individual returns close to the market return. According to Zhou and Anderson (2011), and Chang, Cheng, and Khorana (1999), all agreed that individuals show herding asymmetrically, and investors are more inclined to follow the actions of other people when the market is down. On the other hand, if herd behavior stems from the tendency for people to follow other people's actions (Tversky and Kahneman, 1974), the herd behavior should be observed no matter how our market is (up or down), implying that the herding has symmetric effects. Also, according to Lobao and Serra (2007), market volatility can be caused by uncertainty of future values, which can be witnessed during both extreme down and up markets. More uncertainty implies that less precise information is available to investors. Hence, strong herding behavior emerges.

Given the findings in past studies, we aim to demonstrate that investors show herding behavior in either extreme bull or bear housing market. To this end, the current study, following Christie and Huang (1995), measures Cross Sectional Standard Deviation (henceforth CSSD) as a proxy for the herding behavior. The CSSD captures the degree of return dispersion from the mean. Because investors tend to abandon their beliefs and follow what the market suggests during the periods of market stress, the magnitude of CSSD decreases, implying the presence of herding. Additionally, to capture returns from twenty cities in the US housing market, we use the Case-Shiller index (henceforth CSI). Our empirical research presents evidence in line with the prior study (Christie and Huang, 1995) that the herding behavior does not exert a strong enough impact to change the returns from real estate markets. Rather, our findings support the prediction based on the rational asset pricing model that dispersion increases when the market has large changes in returns.

The rest of this paper is organized as follows. In section II, how our sample including the CSI is constructed is explained. Additionally, the methodologies applied to this research are introduced. Section III summarizes empirical findings. And, lastly, a conclusion based on our findings is addressed in Section IV.

DATA AND EMPIRICAL MODEL

In this section, we provide the rationale for using CSI data and adopting an empirical model for the present study.

Data

Although real estate markets are unique, there are common characteristics between the housing market and the financial market in which investors trade assets. First, real estate transactions are facilitated by buyers and sellers who seek to generate returns. Next, like financial securities, the value of each property is different because of many factors such as condition, location, and so on. Additionally, the real estate market is affected by the overall health of the economy. Furthermore, scholars agree that REITs can be used as a proxy for the performance of real estate property because they capture real estate market factors (McCue and Kling, 1994; Liang, Chatrath and McIntosh, 1996; Lee and Chiang, 2010). These features allow us to apply the empirical methodology in Christie and Huang (1995) to our study.

To investigate the herding effect, we use CSI to conduct the current study for the following reasons. First, the CSI provides the essential data used to compute returns applied to our empirical methodology. Next, rather than focusing on a specific area, multiple cities are used to study a wide range of real estate markets in the United States. The CSI contains information regarding repeated sales from twenty metropolitan areas that is used to compute the equally weighted index.[2] The CSI excludes extraordinary transactions in order to increase reliability. This exclusion includes anomalies, non-arms-length transactions, sales showing the property changes, and suspected data errors.[3] Additionally, to construct the average change in home prices, less weight is given to sales pairs having longer time intervals or price anomalies.[4] A total of 25,616,953 transactions are used to construct the CSI index.[5] This study uses CSI from January 2000 to July 2019 due to the lack of prior data in Chicago. This time frame considered to be enough to reflect the real estate bubble and the effect of the credit crisis. The composite index for twenty cities is used to compute the market return, $R_{m,t}$, in time of t and is then used to test the herding effect on real estate markets.

Empirical Model

According to Christie and Huang (1995), investors show a strong likelihood to forgo relying on their own information and make decisions analogous to the market movement, i.e., the herding behavior. By following market movements, individual investors generate returns not far from the market return, which reduces their return dispersion from the market. Christie and Huang (1995) propose that CSSD is suitable to capture or detect the herding effect. Following them, our study measures CSSD as a proxy for herding behavior – the dispersion. See Equation (1).

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t}-\bar{R}_{m,t}\right)^2}{N-1}} \tag{1}$$

$R_{i,t}$ is the return of repeat sale from city i, at time t. We use two different $\bar{R}_{m,t}$: one is the twenty states (N = 20) cross-sectional equally-weighted average return ($\bar{R}^E_{m,t}$), and the other one is the value-weighted return, $\bar{R}^V_{m,t}$, provided by the CSI. $CSSD^E_t$ and $CSSD^V_t$ are the cross-sectional standard deviation with $\bar{R}^E_{m,t}$ and $\bar{R}^V_{m,t}$, respectively.[6]

Christie and Huang (1995) postulate that CSSD will decrease during down markets if herding behavior exists among individual investors, the asymmetric herding. To test the hypothesis, they examine if CSSD is lower than the average CSSD during extreme market stress.[7] The model to test for herding is given by Equation (2):

$$CSSD_t = \alpha + \beta_1 D^L_t + \beta_2 D^U_t + \varepsilon_t, \tag{2}$$

D_t^L is a binary variable equal to one if the market return on day t lies in the extreme lower tail of the return distribution, zero otherwise. D_t^U is a binary variable equal to one if the market return on day t lies in the extreme upper tail of the return distribution, zero otherwise.[8] Statistically significant negative coefficients for β_1 or β_2 imply that CSSD is lower during either bear or bull markets because of herding behavior.[9] As discussed earlier, our study aims to investigate if herding appears when extreme market returns – *both downside and upside markets* – are perceived.

Christie and Huang (1995) argue that, based on the rational asset pricing model, individual securities react differently to market movements. During periods of market stress, the market returns are volatile, which have a strong influence on individual returns. Therefore, based on the rational asset pricing model, Christie and Huang (1995) expect that an increase in dispersion will emerge during periods of market stress. However, the herding behavior suggests that the dispersion will decrease when the market has large changes in returns. Their empirical results are in favor of the prediction for dispersion offered by the rational asset pricing model.[10] This paper also investigates which prediction is supported by the empirical evidence from real estate markets. To this end, we follow Christie and Huang (1995) and estimate predicted dispersion with expected returns given in Equation (3).

$$\mathrm{E}\left[R_{i,t}\right] = \alpha^i + \beta^i \bar{R}_{m,t} \tag{3}$$

$\mathrm{E}\left[R_{i,t}\right]$ is the expected return of city i, at time t. We run Equation (3) with two different $\bar{R}_{m,t}$ i.e., $\bar{R}^E_{m,t}$ and $\bar{R}^V_{m,t}$. In time t, α^i and β^i are computed using previous 60 months of data prior to time t. $\mathrm{E}\left[R^E_{i,t}\right]$ and $\mathrm{E}\left[R^V_{i,t}\right]$ are the expected returns with $\bar{R}^E_{m,t}$ and $\bar{R}^V_{m,t}$, respectively. We then use the expected return to measure the predicted dispersion by using Equation (1).

EMPIRICAL RESULTS

Table 1 contains the descriptive statistics for each city from the CSI. Our study uses the value-weighted market return (Composite 20 Index returns: henceforth $\bar{R}^{V}_{m,t}$) and the equally-weighted market return (cross-sectional average returns: henceforth $\bar{R}^{E}_{m,t}$) to show that our empirical results are not sensitive to how the market return is constructed. During the sample period, all cities have positive average returns. Charlotte and Dallas have relatively stable housing markets compared to other cities according to the standard deviation of returns while Las Vegas and San Francisco experience higher volatility in real estate markets. In each time t, deviation 1 (deviation 2) is measured as the difference between a city's returns from cross sectional $\bar{R}^{V}_{m,t}$ ($\bar{R}^{E}_{m,t}$) and its average is computed by using Equation (4).

$$Average\ Deviation\ of\ City\ i = \frac{\sum_{t=1}^{n}(R_{i,t}-\bar{R}_{m,t})}{n} \tag{4}$$

where n are months from 2000 to 2019.[11] $R_{i,t}$ is the return of city i, at time t. $\bar{R}_{m,t}$ is either the $\bar{R}^{V}_{m,t}$ from the CSI (Composite 20 cross-sectional return at time t) or the $\bar{R}^{E}_{m,t}$ that is estimated using $\frac{1}{20}\left(\sum_{i=1}^{20}\bar{R}_{i,t}\right)$. The deviation of city i's return from cross-sectional value-weighted mean return (*henceforth* Deviation 1) or cross-sectional equally weighted mean return (*henceforth* Deviation 2) informs that how much the return of each city in time t deviates from the market return at the same time period.[12] Table 1 indicates that Deviation 1 and 2 are close to each other. Negative deviation 1 or 2 implies that return from city i i.e., R_i is lower than the cross-sectional return from the market i.e., $\bar{R}^{V}_{m,t}$ or $\bar{R}^{E}_{m,t}$ respectively. The results from Table 1 suggest that investors will have a lower expected return from ten cities compared to the market return during the sample period.[13]

TABLE 1
DESCRIPTIVE STATISTICS

This table presents descriptive statistics for each city from February 2000 to July 2019. ***Average return*** is the average of returns from city *i* during the sample period. ***Std. D of return*** is the standard deviation of returns from city *i* during the sample period. ***Average Deviation 1*** is the average of "*Deviation 1*" which is the difference between returns from city *i* and the return of Composite 20 Index (value-weighted). ***Std. D of Deviation 1*** is the standard deviation of *Deviation 1*. ***Average Deviation 2*** is the average of "*Deviation 2*" which is the difference between returns from city *i* and the cross-sectional average (equally weighted). ***Std. D of Deviation 2*** is the standard deviation of *Deviation 2*.

Cities	Average return	Std. D of return	Average Deviation 1	Std. D of Deviation 1	Average Deviation 2	Std. D of Deviation 2
Atlanta	0.00191	0.01218	-0.00148	0.00778	-0.00118	0.00715
Boston	0.00351	0.00995	0.00013	0.00627	0.00043	0.00612
Charlotte	0.00217	0.00708	-0.00121	0.00745	-0.00091	0.00675
Chicago	0.00173	0.01292	-0.00165	0.00692	-0.00135	0.00665
Cleveland	0.00109	0.01059	-0.00229	0.00849	-0.00199	0.0078
Dallas	0.00284	0.00798	-0.00055	0.00761	-0.00025	0.00679
Denver	0.00348	0.00845	0.0001	0.00687	0.0004	0.00612
Detroit	0.0012	0.0143	-0.00219	0.00933	-0.00189	0.00895
Las Vegas	0.00298	0.01593	-0.0004	0.01031	-0.0001	0.0105
Los Angeles	0.00458	0.01265	0.0012	0.00518	0.0015	0.00604
Miami	0.00391	0.01303	0.00052	0.00704	0.00082	0.0075
Minneapolis	0.00263	0.01436	-0.00075	0.00819	-0.00045	0.00783
New York	0.00302	0.00864	-0.00037	0.00528	-0.00007	0.00597
Phoenix	0.00295	0.01517	-0.00043	0.00929	-0.00013	0.00919
Portland	0.00382	0.01003	0.00044	0.00607	0.00074	0.00529
San Diego	0.00423	0.01266	0.00085	0.00636	0.00115	0.00702
San Francisco	0.00439	0.01624	0.001	0.00923	0.0013	0.00933
Seattle	0.00409	0.01102	0.0007	0.00708	0.001	0.0064
Tampa	0.00344	0.01183	0.00006	0.00598	0.00036	0.00597
Washington	0.00372	0.01135	0.00033	0.00457	0.00063	0.00513

To investigate the presence of herding behavior, we run Equation (2) with the lower and upper tails of the market return distribution (D_t^L and D_t^U), using two criteria (1% and 5%) to identify the periods of down- and up-markets. We exclude the years 2007 – 2008 from the sample period in order to show that the effect of herding behavior is not driven by the financial crisis. Two market returns ($\bar{R}_{m,t}^V$ and $\bar{R}_{m,t}^E$) are used to create two different dependent variables ($CSSD_t^V$ and $CSSD_t^E$). Empirical results are presented in Panel B of Table 2.[14]

TABLE 2
EMPIRICAL RESULTS

This table presents coefficients estimated by using Equation (2): $CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$. We constructed two *CSSDs*. $CSSD_t^E$ and $CSSD_t^V$ are the cross-sectional standard deviation with $\bar{R}_t^E$ and $\bar{R}_t^V$, respectively. $\bar{R}_t^E$ is the cross-sectional average return of twenty states (N = 20), equally-weighted return. $\bar{R}_t^V$ is the value-weighted return provided by the CSI. Accordingly, the dummy variables are set up by using both $\bar{R}_t^E$ and $\bar{R}_t^V$: D_t^{LE} and D_t^{UE} with $\bar{R}_t^E$ and D_t^{LV} and D_t^{UV} with $\bar{R}_t^V$. Low and upper tails of the market return are based on two criteria: 1% or 5%. Panel A has the sample period from January 2000 to July 2019. And, Panel B displays the estimates with the sample period without the financial crisis: years 2007 and 2008. ***, ** and * represent statistical significance at 1%, 5% and 10% level respectively.

Panel A

Dependent variable	Criterion	α	β_1	β_2	*Adj.* R^2 *(Observations)*
$CSSD_t^V$	1%	0.0069***	0.0061***	0.0026***	0.0562
		(0.0000)	(0.0002)	(0.0001)	(4680)
	5%	0.0066***	0.0052***	0.0038***	0.195
		(0.0000)	(0.0002)	(0.0002)	(4680)
$CSSD_t^E$	1%	0.0067***	0.0050***	0.0041***	0.0547
		(0.0000)	(0.0001)	(0.0002)	(4680)
	5%	0.0064***	0.0051***	0.0039***	0.200
		(0.0000)	(0.0002)	(0.0002)	(4680)

Panel B

Dependent variable	Criterion	α	β_1	β_2	*Adj.* R^2 *(Observations)*
$CSSD_t^V$	1%	0.0066***	0.0065***	0.0029***	0.0360
		(0.0000)	(0.0000)	(0.0001)	(4200)
	5%	0.0064***	0.0077***	0.0039***	0.189
		(0.0000)	(0.0002)	(0.0002)	(4200)
$CSSD_t^E$	1%	0.0064***	0.0058***	0.0044***	0.0690
		(0.0000)	(0.0001)	(0.0002)	(4200)
	5%	0.0062***	0.0074***	0.0041***	0.193
		(0.0000)	(0.0003)	(0.0002)	(4200)

Table 2 displays the results of estimating Equation (2). Our empirical results are in line with findings in Christie and Huang (1995) that the herding behavior is not manifest in the residential housing market. Both coefficients on D_t^L and D_t^U have positive signs that are statistically significant at 1% level, which are on the side of the rational asset pricing model. A potential explanation could be the unique characteristics of real estate markets where the market value of a property is much higher than that of financial securities traded in the market. And, real estate investors hold properties for quite a long time. Because of lengthy holding period and high value, investors are not able to diversify the volatility of return resulting from large changes in property prices, which is reflected in the increasing dispersion.

It is worth to note that Table 2 shows the asymmetric behavior of dispersion in the real estate market consistent with Christie and Huang (1995). However, unlike findings in the prior study, the dispersion is larger when the real estate market is down regardless of the different criteria or dependent variables.[15] Table 3 provides more detailed information regarding the magnitude of actual dispersion and their associated market returns: upper and lower tails with 5%.

TABLE 3
ACTUAL AND PREDICTED DISPERSIONS

This table presents the ten largest negative and ten largest positive market returns and their associated actual and predicted dispersions. Actual dispersions, $CSSD_t$ is measured by using Equation (1): $CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t}-\bar{R}_t)^2}{N-1}}$. Actual $CSSD_t^E$ and $CSSD_t^V$ are computed by using $\bar{R}_t^E$ with $R_{i,t}$ and $\bar{R}_t^V$ with $R_{i,t}$, respectively. $R_{i,t}$ is collected from the CSI. Predicted $CSSD_t^E$ and $CSSD_t^V$ are estimated by using $\bar{R}_t^E$ with $\mathrm{E}[R_{i,t}^E]$ and $\bar{R}_t^V$ with $\mathrm{E}[R_{i,t}^V]$, respectively. Both $\mathrm{E}[R_{i,t}^E]$ and $\mathrm{E}[R_{i,t}^V]$ are computed by using Equation (3): $\mathrm{E}[R_{i,t}] = \alpha^i + \beta^i \bar{R}_{m,t}$.

Date	Market return	Actual $CSSD_t^V$	Predicted $CSSD_t^V$	Actual $CSSD_t^E$	Predicted $CSSD_t^E$
January 2009	-0.02790	0.01309	0.01310	0.01235	0.01307
February 2008	-0.02612	0.01441	0.01302	0.01426	0.01285
December 2008	-0.02563	0.01142	0.01263	0.01084	0.01257
January 2008	-0.02319	0.01151	0.01160	0.01147	0.01145
November 2008	-0.02271	0.00640	0.01189	0.00629	0.01179
February 2009	-0.02207	0.01245	0.01023	0.01204	0.01023
October 2008	-0.02196	0.01081	0.01222	0.01062	0.01210
March 2008	-0.02137	0.01587	0.01116	0.01571	0.01103
March 2009	-0.02131	0.01658	0.00988	0.01653	0.00988
December 2012	-0.02101	0.00950	0.01103	0.00933	0.01083
Average		*0.01220*	*0.01168*	*0.01194*	*0.01158*
March 2005	0.01569	0.01171	0.00715	0.01116	0.00665
May 2005	0.01612	0.00871	0.00740	0.00869	0.00696
April 2005	0.01622	0.00949	0.00742	0.00946	0.00693
July 2009	0.01655	0.01248	0.00676	0.01247	0.00675
July 2013	0.01831	0.00698	0.00555	0.00696	0.00552
June 2013	0.02179	0.00638	0.00663	0.00638	0.00659
June 2012	0.02270	0.01282	0.00822	0.01262	0.00821
May 2012	0.02368	0.01094	0.00837	0.01079	0.00836
May 2013	0.02509	0.00851	0.00780	0.00851	0.00774
April 2013	0.02560	0.00907	0.00817	0.00904	0.00810
Average		*0.00971*	*0.00735*	*0.00961*	*0.00718*

If lower dispersion during up markets is attributed to the herding effect, the dispersion of predicted returns should be larger than the actual dispersion.[16] The results from Table 3 reveals that the predicted dispersion, *Predicted* $CSSD_t^V$ and *Predicted* $CSSD_t^E$, are lower on average than the actual ones. This confirms that our empirical results are more consistent with the predictions for dispersion offered by rational asset pricing models.

CONCLUSION

Herding emerges when individuals abandon their own beliefs and mimic or follow other people's decisions or actions. We investigate if housing market investors exhibit herding behavior. The empirical tests using CSI data are executed in this study. The literature examining the relationship between the herding and the real estate market is limited. Consequently, our study utilizes the empirical structure used to explore the herding effect on REITs.

With herding, the dispersion in returns during periods of market stress is expected to be relatively low because investors tend to follow the market consensus. On the contrary, the rational asset pricing model predicts that the dispersion is larger because of the different sensitivities of assets to large changes in market returns. We present evidence that dispersion reflects the large changes in market returns as the rational asset pricing model predicts, with the potential explanation being that, because of the high price of real estate property, imitating the actions of other people would entail great risk if those actions turn out to be wrong. Also, closing a property deal can take a long time, which hinders investors benefiting from risk diversification. Therefore, investors prefer following the market consensus to imitating the actions of other people.

We also investigate the precited CSSD to find out if asymmetric dispersion results from herding effects. The comparison of the actual CSSD to the predicted CSSD confirms that the pattern of returns from real estate markets supports the predictions offered by rational asset pricing models.

ENDNOTES

1. More information about two main streams can be found in notable studies conducted by Clement and Tse (2005), Gleason and Lee (2003), Graham (1999), and Trueman (1994).
2. Case-Shiller Index for twenty metropolitan cities is a data as of October 1, 2019. In our study, we use the CSI with the Composite of 20 metro areas.
3. Non-arms-length transactions can be defined as any transaction between family members. Property type change is any change in designation of property type such as change from single-family homes to condominiums.
4. CSI uses a three-month moving average algorithm, accumulating home sales pairs in consecutive three-month periods so that CSI can offset delays occurring in the flow of sales price data from county deed recorders.
5. In 2000, the index uses 22,007,168 transactions: S&P CoreLogic Case-Shiller Home Price Indices Methodology (April 2019).
6. To test if CSSD changes depending on how $\bar{R}_{m,t}$ is computed, we measure the $\bar{R}_{m,t}$ in two different ways.
7. Market stress is defined as periods of large price movements in either up or down direction which entails large changes in returns.
8. The dummy variables are set up by using both $\bar{R}_{m,t}^E$ and $\bar{R}_{m,t}^V$: D_t^{LE} and D_t^{UE} with $\bar{R}_{m,t}^E$ and D_t^{LV} and D_t^{UV} with $\bar{R}_{m,t}^V$.
9. Following Christie and Huang (1995), our study uses 1%, and 5% to detect the extreme market returns.
10. Christie and Huang (1995) show statistically significant coefficients on D_t^L and D_t^U with positive signs, implying there is more dispersion during the periods of extreme markets. Also, their results indicate that individual returns have more dispersion when the market is bullish.
11. There are total 150 months with returns.
12. This research assumes that the whole market consists of twenty cities used in CSI.
13. These cities are Atlanta, Charlotte, Chicago, Cleveland, Dallas, Detroit, Las Vegas, Minneapolis, New York, and Phoenix.

14. Panel A of Table 2 show the coefficient estimates by using the whole sample period.
15. Christie and Huang (1995) report that the dispersion is greater when the market is bullish.
16. We estimate the predicted returns by using Equation (3).

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