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Herding Spillover Effects in US REIT Sectors

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Abstract

This study examines the sector-level herding behavior and herding spillover across eleven US-listed Real Estate Investment Trusts (REITs) sectors from January 4, 1999 to December 8, 2023. A standard linear model shows no herding behavior for all sectors, except for the lodging and resorts sector; whereas, a more robust quantile regression reveals significant herding in all eleven sectors and for the overall market at the lower tails of the distribution of cross-sectional return dispersion. The time-varying parameter ordinary least squares (TV-OLS) approach demonstrates spasmodic switches between herding and anti-herding behaviors during the sample period across all sectors and the overall market. A spillover analysis highlights significant herding spillover effects across REIT sectors. Evidence of negative spillover effects with portfolio diversification benefits is driven by the stable demand for essential REITs, such as residential and healthcare, and the structure of long-term lease contracts for infrastructural, industrial, office, diversified, and regional malls REITs. Our findings entail implications for the decisions of retail and institutional investors and for the insights of regulatory authorities and policymakers.

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1. Introduction

Investing in real estate has become easier and more accessible for both retail and institutional investors since the introduction of Real Estate Investment Trusts (REITs) in 1960. The success of REITs as an attractive alternative to traditional financial assets such as stocks and bonds is witnessed by their astonishing growth in total numbers and size. Official data from the National Association of Real Estate Investment Trusts (NAREIT) indicate that the number of REITs has grown from 120 in two countries to 940 in more than forty countries and regions over the past three decades. In the US, more than 170 million citizens invest in REITs directly or through a retirement account. The total market value of US REITs has grown from nearly 1.5 billion USD in 1971 to an astonishing 1.37 trillion USD in 2023.

REITs could be characterized as 'hybrid' securities since they allow investors to own a part of a portfolio of income-producing real estate assets while they enjoy at the same time the benefits of increased liquidity, potential of higher returns, and diversification opportunities that can be found in traditional financial assets (Hoesli and Oikarinen, 2012). It is worth mentioning that public REITs have been found to display characteristics similar to those of small cap stocks (Clayton and MacKinnon, 2003) while their performance is likely to be affected by the developments in the stock market in general, leading to situations of overreaction/underreaction (Liu and Lu, 2020), feedback trading (Balomenou et al., 2021), and herding. REITs are classified as equity and mortgage, depending on the asset composition of their underlying portfolio. In particular, market authorities, various associations such as NAREIT, and investment managers group REITs into sectors following property types (Anderson et al., 2015). Each REIT sector has unique characteristics and distinct demand and supply elasticities. In this regard, two prominent examples the hotels/lodging sector and the Residential sector, which exhibit different sensitivities to economy-wide fluctuations. In particular, hotel and lodging resorts that derive their income mostly from seasonal and short-term agreements exhibit larger cyclicality than the apartment sector, which is characterized by a smoother flow of economic rents (Anderson et al., 2003).

Given listed REITs tend to behave like small-cap stocks, the stock market literature offers support to a hypothesized link between the market size of firms and the intensity of the herding phenomenon. In fact, Lakonishok et al. (1992) provide evidence in favor of the hypothesis of more intense herding among small companies compared to large stocks. Further support to this hypothesis is provided by Choi and Sias (2009) and Venezia et al. (2011). In light of this, it is worth exploring the extent of herding behavior in US REITs, shedding light on potential spillover effects of herding phenomenon across REIT sectors.

Since the seminal studies by Christie and Huang (1995) and Chang et al. (2000), the herding behavior in financial markets has been heavily researched. In financial economics, herding involves investors' irrational affinity to imitate other investors' trading behavior and patterns, ignoring their beliefs and private information. Generally, imitating investors completely opposes the copied trading behavior (Spyrou, 2013). Herding is more likely when markets are highly volatile, in uncertain economic conditions, and investors lack credible trading signals; hence, they mimic other investors (Ngene et al., 2017). The correlated trading activities among investors drive asset prices above the fundamental price, causing asset price bubbles. According to Shiller (2015), herding is closely related to irrational exuberance, overenthusiasm, and asset price bubbles.

Compelling evidence of herding behavior has been documented in various assets, including mutual funds (Frey et al. 2014; Borensztein and Gelos (2003); and Lakonishok et al. (1992), government and corporate bonds (Cai et al., 2019; and, Oehler and Chao,2000), commodities (Cakan et al., 2019 and Junior et al., 2019), stocks (Hasan et al., 2023; Bohl et al., 2017; Litimi et al., 2016; Balcilar et al., 2014; Chang et al., 2000; and Christie and Huang, 1995) and real estate[5] (Lesame et al., 2024; Akinsomi et al., 2018; Ngene et al., 2017; Babalos et al., 2015; Ro and Gallimore, 2014 ; Zhou and Anderson, 2013; and Philippas et al., 2013). While herding behavior in the REITs market is well established (see, inter alia, Philippas et al. 2013; Zhou and Anderson, 2013), the issue of herding spillover across REIT sectors has not been investigated. An important characteristic of the REIT sectors is that they provide investors with a greater variety and help investors diversify away the risk associated with individual REITs. In particular, the expansion of REITs to the so-called non-traditional REITs, such as healthcare, self-storage, and timber, offers more opportunities for income-generating properties (Newell and Wen, 2006). Therefore, the existence of herding spillovers between REIT sectors could undermine the benefits of diversification and the stability of the REIT market, and this is one major concern addressed in the current study.

[5] These include studies on herding behavior in the real estate investment trusts (REITs), Real estate mutual funds, and direct housing markets.

In this study, we first consider the herding behavior in the US REITs market, focusing on a very popular segment of the securitized real estate sector, using data from January 4, 1999 to December 8, 2023. Then, we investigate herding spillover among the various sectors of US equity REITs that own and operate illiquid but income-generating commercial real estate property.

Among the underlying physical assets owned by REITs are (i) traditional core properties such as office buildings, residential complexes, industrial buildings, self-storage and warehouses, healthcare facilities, hotels and resorts, and retail centers (outlet, regional and shopping malls), (ii) specialized assets such as movie theaters, timberland, farmland, telecommunications towers, data centers, and outdoor advertising sites. The REITs market is, therefore, highly diversified. The dispersed and segmented nature of the real estate market, heterogeneous assets, unique and localized markets, high information search and transaction costs, and long transaction consummation time make the real estate market highly uncertain, making it more susceptible to herding behavior. Kurlat (2016) shows that buyers in the real estate market have divergent information about the quality of the property and neighborhoods, slowing the price formation process, increasing market uncertainty, and herding behavior.

Risk and herding spillovers across the REITs sub-sectors and regions can be attributable to several factors, as described below:

(i) Differences in fundamental drivers of REIT subsectors. The performance of REITs is innately dependent on the performance (cash flows) of the underlying illiquid assets (Hoesli and Oikarinen, 2016). However, the performance of the underlying property is inherently dependent on macroeconomic fundamentals, making REITs' performance partly and indirectly dependent on macro factors. Lee et al. (2018) find that the volatility of REITs is sensitive and strongly positively related to the volatility of interest rates, inflation rates, GDP, foreign exchange, and M2 money. Therefore, a macroeconomic shock to one sub-sector will likely propagate to other subsectors due to co-movement effect. However, REIT subsectors may exhibit significant differences in short- and long-term returns due to differences in fundamental drivers of performance for each sector. For example, a shift towards online shopping will result in a long-term performance of retail REITs and improve the long-term performance of industrial REITs. The rapid expansion of wireless data usage may generate high returns for telecommunication (infrastructure) tower REITs. Data center REITs will significantly benefit from the expanding need for high-quality space for the IT infrastructure, such as servers for cloud computing, data management and processing, switches, routers, and network devices for directing internet traffic, and hard and solid-state drives for data storage. Such unique drives may cause low correlation between specialized REITs and traditional core properties (such as office, industrial, and residential) returns. These differences also suggest risk and herding cross-subsector spillovers.

(ii) Local economic shocks propagating to neighboring regions. A shutdown of a major local industry, the largest employer, affects a REIT that owns local properties in that location. First, industrial REITs will be affected by the closure. Second, the locals' potential loss of jobs and income will negatively impact retail REITs. As the locals relocate in search of new jobs elsewhere, local residential house prices will decline, and the supply of vacant residential premises will rise, resulting in a loss of rental income. Service providers with local offices will shut down, increasing the supply of vacant offices. Overall, such a shock will induce cross-subsector risk and herding spillovers.

(iii) Regional shock spillover. A decline in residential property prices in a region that has experienced a major economic shock will likely spread to neighboring regions. Such a regional spillover comprises a transmission of risk from one REIT to another.

(iv) REITs are highly leveraged due to their heavy reliance on debt to finance their underlying real estate assets. Adams et al. (2015) and Cici et al. (2011) find that REITs' higher leverage is related to higher risk and stronger response to risk spillovers.

(v) The REITs market is dominated by institutional investors, however the information opaqueness of REITs makes their returns often mirror those of small-cap stocks (Yung and Nafar, 2017; Ngene and Wang, 2024). Accordingly, REITs are particularly attractive to retail investors (Baker and Wurgler, 2007). Most REIT investors own similar REIT properties in multiple regions. The regional cross-holdings provide intra-sector diversification and a high degree of systematic information. The regional cross-holdings also enable cross-asset learning, generating feedback loops and herding multiplier effects (Cespa and Foucault, 2014; Chiang, 2010). Different REIT sectors face similar macroeconomic risks, such as interest rate risk, market liquidity risk, leverage risk, inflation risk, economic growth risk, and commonality of financing sources risk. Therefore, a shock in a major regional market (gateway MSAs) or REIT sector tends to propagate to other REITs because of the informative nature of REIT price declines, resulting in herding behavior, correlated equity returns, and reduced diversification benefits. Herding forces can become increasingly synchronized across the REIT sectors. Furthermore, commonality in herding behavior may prove catalytic in triggering regional and national crises in the REITs and housing markets. In this regard, Economou et al. (2011) report a significantly positive relationship between the cross-sectional absolute deviation (CSAD) measures across the Spanish and Portuguese markets. Mobarek et al. (2014) find that the CSAD of one market can be partly explained by the CSAD of other neighboring markets, suggesting the susceptibility to CSAD to positive co-movement. Given the heterogeneity across REIT sectors, we therefore test for potential transmission of herding effects from a given REIT sector to other REIT sectors.

The main results show significant herding in all eleven REIT sectors and for the overall market at the lower tails of the distribution of cross-sectional return dispersion. A time-varying parameter analysis demonstrates spasmodic switches between herding and anti-herding behaviors during the sample period across all sectors and the overall market. Notably, we reveal significant herding spillover effects between REIT sectors.

The rest of the paper proceeds as follows: Section 2 briefly reviews the relevant studies on real estate market herding. Section 3 outlines the data and methodology used. Section 4 presents and discusses the results. Section 5 concludes the paper.

2. Literature review: Herding in the real estate markets

The diversification and inflation-hedging benefits of REITs have become increasingly popular among asset managers and investors, attracting growing interest in academic research. Here, we offer a compendium of relevant studies on herding behavior in the REITs and housing markets.

Philippas et al. (2013) examine the presence of herding behavior from January 2004 to December 2011 in eight sub-sectors of the US REIT market, using the Cross-Sectional Absolute Deviation (CSAD) model of Chang et al. (2000). They show evidence of asymmetric (based on extreme negative and positive returns) herding behavior and identify deterioration of investors' sentiment and adverse macro-shocks to REIT funding conditions as the significant drivers of the herding behavior. Their results align with the findings of Zhou and Anderson (2013).

Ro and Gallimore (2014) investigate herding, momentum trading, and performance of 159 real estate mutual funds (REMFs). They find a lower level of herding for REIT stocks than non-REIT stocks, which they attribute to higher transparency in REIT trading. Herding behavior in REMF is characterized by "disposition effects," which capture managers' tendency to sell winners. They suggest that neither momentum nor herding trading is discernibly superior as an investment strategy for REMFs.

Using a Markov regime-switching model and US-listed REITs data, Babalos et al. (2015) document the existence of herding behavior under the extreme volatility (crash) regime, whereas the results from a static model reveals no evidence of herding. They also found that anti-herding (herding) behavior is significant in the crash regime for each REIT sub-sector.

Ngene et al. (2017) use monthly direct housing prices to investigate spatial and time-varying herding behavior in the US residential housing market. While the time-invariant linear model shows no evidence of herding behavior, regime-switching and quantile regression models reveal asymmetric herding behavior that vastly varies across regimes, regions, and conditional distributions. Herding is relatively stronger during the bull market. Further, they show that stress in the financial markets, economic recessions, and uncertainty of economic policies amplify herding behavior. They conclude that the presence of herding offers little hope of portfolio diversification based on the geographically dispersed housing market.

Akinsomi et al. (2018) employ the CSAD model and find herding behavior, directional asymmetry, and a linear relationship between volatility and herding in the Turkish REITs market. They show that herding is highly persistent and increases during stressed market conditions.

Lesame et al. (2024) use the quantile-on-quantile and probit model to investigate herding behavior in international REITs markets due to the elevated 2020 COVID-19-induced economic uncertainty. Based on REITs data of 27 developed and developing countries, they find consistent evidence of herding formation in international REITs markets based on static and time-varying estimates. International herding behavior, induced by the economic uncertainty around the 2020 pandemic, is mainly driven by herding in developed markets' REITs. A quantile-on-quantile regression reveals that herding intensified with elevated uncertainty during the pandemic.

In summary, herding behavior in the REIT markets generally strengthens during extreme market downturns characterized by high volatility and uncertainty. Relative to alternative investment strategies, herding is a suboptimal investment strategy. It can also explain how uncertainty and investor sentiment can engender real estate bubbles. The bursting of asset price bubbles results in a significant loss of investors' wealth. However, the related literature lacks a spillover analysis of herding behavior across REIT sectors, despite the unique features that characterize REIT sectors.

3. Data and Methodology

3.1 Description of the US REITs market

Most REITs are listed and their shares are publicly traded on organized stock exchanges such as the New York Stock Exchange (NYSE). The two most common types of REITs are equity REITs and mortgage REITs. Equity REITs seek to generate income through buying/selling real estate properties or collecting rents from properties they own. Portfolios of mortgage REITs consist of mortgages or mortgage securities associated with commercial and/or residential properties. The popularity of REITs among investors in the US and around the globe is indisputable. According to the US National Association of REITs (NAREIT): '*Public equity REITs constitute the majority of today's REIT market and help power the U.S. economy. They own more than $2.5 trillion of real estate assets in the U.S., including more than 580,000 structures in all 50 states and the District of Columbia.'* REITs derive their popularity among investors mainly from legal requirements to distribute 90% or more of their income as dividends and due to their returns' low correlation with other assets, serving as a portfolio diversifier for institutional and retail portfolios.

Table 1 presents the total number and total market value in millions of USD of all US-listed REITs from 1971 to 2023. The total number of US-listed REITs in 2023 stood at 197 REITs, while the total market value of US-listed REITs reached nearly 1.37 trillion USD, growing from around 1.5 billion USD in 1971. Table 1 also reports the breakdown of public US REITs into three categories: Equity, Mortgage, and Hybrid. Equity REITs dominate the sector of US public REITs. In 2023, there were 156 distinct US Equity REITs, with a total market valuation of nearly 1.3 trillion USD, whereas the number of mortgage REITs was 41, with a total value of 60.5 billion USD.

Table 1: Historical Breakdown of US-Listed REITs and Market Capitalization in USD Billions

	Equity		Mortgage		Hybrid		All	
Year	Number	Market cap	Number	Market cap	Number	Market cap	Number	Market cap
1971	12	0.332	12	0.571	10	0.592	34	1.494
1972	17	0.377	18	0.775	11	0.729	46	1.881
1973	20	0.336	22	0.517	11	0.540	53	1.394
1974	19	0.242	22	0.239	12	0.232	53	0.712
1975	12	0.276	22	0.312	12	0.312	46	0.900
1976	27	0.410	22	0.416	13	0.483	62	1.308
1977	32	0.538	19	0.398	18	0.592	69	1.528
1978	33	0.576	19	0.340	19	0.496	71	1.412
1979	32	0.744	19	0.377	20	0.633	71	1.754
1980	35	0.942	21	0.510	19	0.847	75	2.299
1981	36	0.978	21	0.541	19	0.920	76	2.439
1982	30	1.071	20	1.133	16	1.094	66	3.299
1983	26	1.469	19	1.460	14	1.329	59	4.257
1984	25	1.795	20	1.801	14	1.489	59	5.085
1985	37	3.270	32	3.162	13	1.241	82	7.674
1986	45	4.336	35	3.626	16	1.962	96	9.924
1987	53	4.759	38	3.161	19	1.782	110	9.702
1988	56	6.142	40	3.621	21	1.673	117	11.435
1989	56	6.770	43	3.536	21	1.356	120	11.662
1990	58	5.552	43	2.549	18	0.636	119	8.737
1991	86	8.786	28	2.586	24	1.596	138	12.968
1992	89	11.171	30	2.773	23	1.968	142	15.912
1993	135	26.082	32	3.399	22	2.678	189	32.159
1994	175	38.812	29	2.503	22	2.991	226	44.306
1995	178	49.913	24	3.395	17	4.233	219	57.541
1996	166	78.302	20	4.779	13	5.696	199	88.776
1997	176	127.825	26	7.370	9	5.338	211	140.534
1998	173	126.905	28	6.481	9	4.916	210	138.301
1999	167	118.233	26	4.442	10	1.588	203	124.262
2000	158	134.431	22	1.632	9	2.652	189	138.715
2001	151	147.092	22	3.991	9	3.816	182	154.899
2002	149	151.272	20	7.146	7	3.519	176	161.937
2003	144	204.800	20	14.187	7	5.225	171	224.212
2004	153	275.291	33	25.964	7	6.639	193	307.895
2005	152	301.491	37	23.394	8	5.807	197	330.691
2006	138	400.741	38	29.195	7	8.134	183	438.071

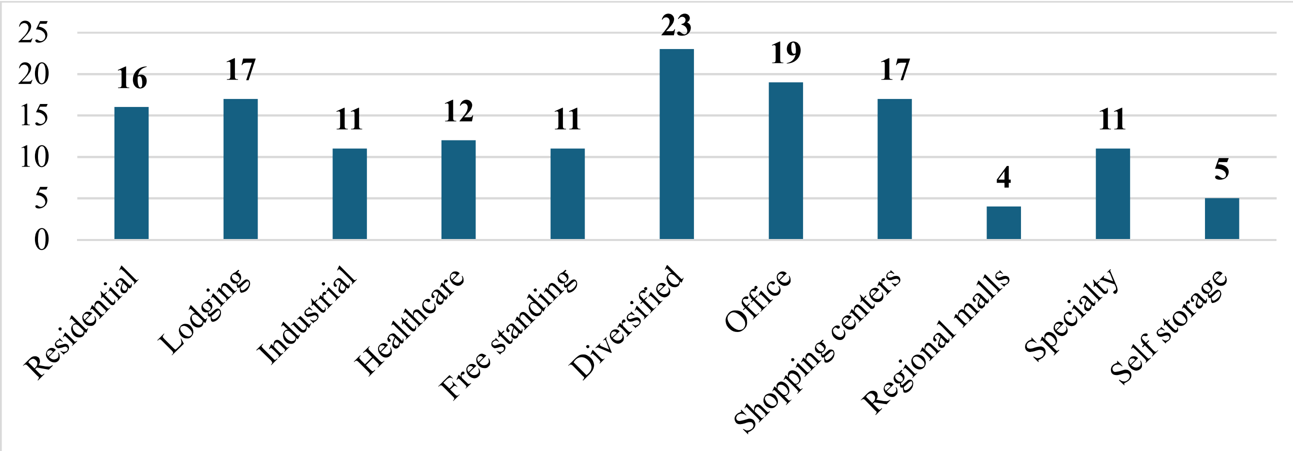
2007	118	288.695	29	19.054	5	4.260	152	312.009
2008	113	176.238	20	14.281	3	1.133	136	191.651
2009	115	248.355	23	22.103	4	0.741	142	271.199
2010	126	358.908	27	30.387		0.000	153	389.295
2011	130	407.529	30	42.972		0.000	160	450.501
2012	139	544.415	33	59.000		0.000	172	603.415
2013	161	608.277	41	62.057		0.000	202	670.334
2014	177	846.410	39	61.017		0.000	216	907.428
2015	182	886.488	41	52.365		0.000	233	938.852
2016	184	960.193	40	58.537		0.000	224	1,018.730
2017	181	1065.948	41	67.750		0.000	222	1,133.698
2018	186	980.315	40	67.326		0.000	226	1,047.641
2019	179	1245.878	40	82.928		0.000	219	1,328.806
2020	182	1184.150	41	65.036		0.000	223	1,249.186
2021	175	1664.524	42	75.754		0.000	217	1,740.277
2022	162	1214.823	44	55.861		0.000	206	1,270.684
2023	156	1313.735	41	60.486		0.000	197	1,374.221

Source: NAREIT

We employ daily data on US Equity REITs that were in continuous operation for the period from January 4, 1999 to December 8, 2023. Closing prices for our sample US REITs are retrieved from DataStream. The number of our sample REITs varies since we include REITs for as long as they are in operation. We start our analysis with a total number of 67 REITs, and we end up with a maximum number of 146 REITs.

Figure 1 presents a sector breakdown of US equity REITs under study. Notably, the reported numbers refer to the maximum number of REITs belonging to each category. NAREIT reports the following breakdown of US listed equity REITS into sectors (subsectors): Industrial/Office (Office, Industrial), Retail (Shopping centres, Regional Malls, Free Standing) Residential (Residential, Manufactured Homes, Single Family homes), Diversified, Health Care, Lodging/resorts, Self -storage, Specialty, Timber, Infrastructure, Data Centres. To ensure the highest precision for our inference, we examined the behaviour of each sub-sector separately from the retail sector. We also separately analyse industrial and office subsectors as distinct subsectors. Finally, the residential and apartment subsectors are combined due to a low number of REITs (fewer than 3) in some cases. The same applies to the Timber and Data Centres subsectors.

Figure 1: REITs Breakdown by Sectors



Source: NAREIT

3.2 Methodology

Following a streamlining of relevant studies, herding behavior in our study is captured by means of the Chang et al. (2000, CCK hereafter) model, which was built on the work of Christie and Huang (1995), assuming that the Cross-Sectional Absolute Deviation of stock returns (CSAD) should be linearly related to market return. In the context of the CCK model, stock returns are generated by the CAPM, and any statistically significant deviation from the asset pricing model's prediction constitutes herding behavior. In other words, if investors tend to discard their own information and herd, especially during high absolute returns, then the cross-sectional dispersion of the returns will no longer respond linearly to market returns. In such cases, we expect cross-sectional deviation of returns to conform to Eq. (1) and the β_2 coefficient to assume a negative sign (see Gebka and Wohar, 2013, for further discussion). In the absence of herding, the β_2 coefficient is expected to be zero or statistically insignificant, while a positive and statistically significant non-linear term implies that cross-sectional absolute deviation is an increasing function of market return, which has been termed as anti-herding behavior (Gebka and Wohar, 2013; Babalos and Stavroyiannis, 2015).

The CCK model takes the form:

$$CSAD_{i,t} = \beta_0 + \beta_1 \left| R_{M,i,t} \right| + \beta_2 R_{M,i,t}^2 + e_{i,t} \tag{1}$$

where $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{it} - R_{m,t}\right|$; $R_{i,t}$ is the return of the i-th asset at time t; and $R_{m,t}$ is the average of the $R_{i,t}$'s of US REITs.

In the context of our study, CSAD is computed from all REITs under consideration, and market return is proxied by the return of an equally weighted portfolio of REITs. The descriptive statistics of the variables of interest, namely, CSAD, for each sector and the whole sample of US equity REITs, are presented in Table 2. CSAD variables deviate from normal distribution conditions as reflected by the statistically significant Jarque-Bera statistics - positive skewness (asymmetry), and excess kurtosis-, indicating the presence of extreme CSAD values.

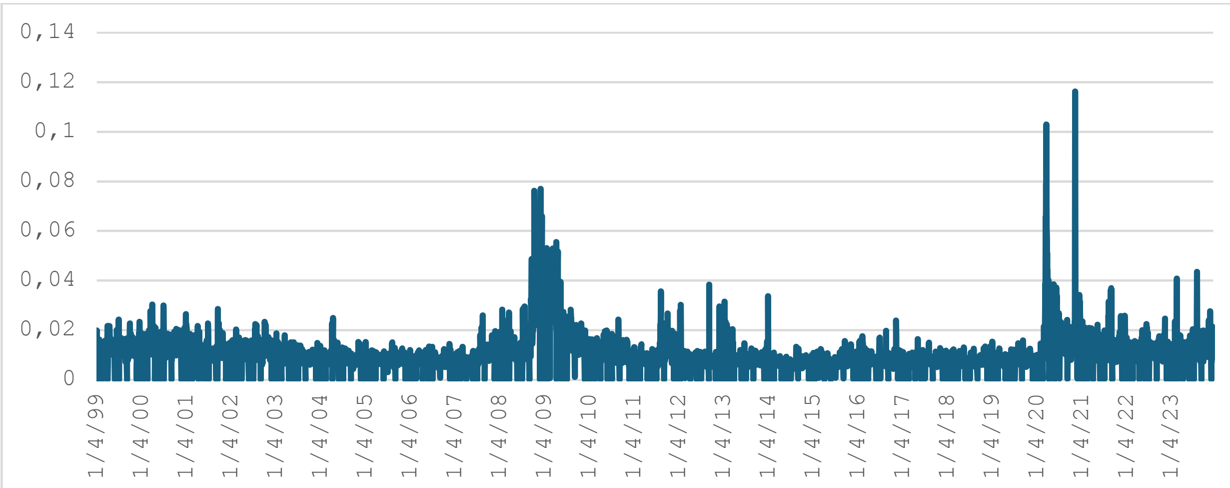
Table 2: Descriptive statistics of CSAD at sector level and overall (All sectors)

	Mean	Maximum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	N
Residential	0.0078	0.091	0.006	4.011	31.408	236176***	6505
Diversified	0.0136	0.198	0.012	5.894	59.654	907631***	6505
Freestanding	0.0077	0.232	0.008	8.106	159.268	6690019***	6505
Healthcare	0.0088	0.088	0.007	3.130	21.369	102071***	6505
Industrial	0.0079	0.121	0.007	5.102	47.626	567999***	6505
Lodging/Resorts	0.0136	0.156	0.012	3.483	23.795	130354***	6505
Office	0.0080	0.100	0.006	4.243	37.044	333647***	6505
Regional malls	0.0066	0.145	0.007	4.619	42.354	442910***	6505
Self-storage	0.0080	0.099	0.007	3.085	19.785	86681***	6505
Shopping malls	0.0079	0.086	0.006	4.134	29.934	215157***	6505
Specialty	0.0127	0.177	0.010	4.330	38.663	365053***	6505
All	0.0108	0.116	0.007	4.007	34.029	278369***	6505

Note: The sample period is from January 4, 1999 to December 8, 2023.

Figure 2 presents the behavior of CSAD for the same period under consideration. The CSAD measure exhibits a steady evolution, with some noteworthy spikes. These cases reflect deviations from the market consensus that are significantly increasing and might be related to important events associated with the regulatory and tax reforms. We refer inter alia to the following dates: July 2008 to August 2009, March 2020, and November 2020. The sub-sample period, July 2008 to August 2009, coincides with the turbulence inflicted on the capital markets by the US Subprime mortgage crisis. Moreover, according to the National Association of Real Estate Investment Trusts (NAREIT), the US Congress validated the REIT Investment and Diversification Act (RIDEA) in July 2009, making REITs more attractive as an investment tool. It should be noted that the year 2020 marked the final amendment to the tax treatment of income received in the form of REIT dividends for individuals. [6] Taken together, these observations could lead to a more intense and correlated trading behavior from investors in the US REIT market.

Figure 2. Cross-Sectional Absolute Deviation (CSAD) for the US REITs (1999–2023).



Source: Authors' calculations

Besides the traditional OLS method, we employ the quantile regression (QR) advocated by previous studies (e.g., Economou et al., 2016). Developed by Koenker and Bassett (1978), the QR established coefficient estimates for different quantiles of the dependent variable, in our case CSAD. The existence of skewness, kurtosis, and non-normal distribution of CASD of all sectors justifies the deployment of QR. Formally, the τ-th conditional quantile function of the distribution of the dependent variable, CSAD, is defined as follows:

$$QY_i(\tau|x) = x_i'\beta \quad (2)$$

In Eq. (2), Y_i is a dependent variable (CSAD), x_i is a vector of explanatory variables, and β is a vector of coefficients. The $\hat{\beta}_{(\text{quantile })}$ estimator results from the minimization of weighted residuals:

$$\hat{\beta}_{(\text{quantile } \tau)} = \arg\min \sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta) \quad (3)$$

where ρ_τ is a check function (weighting factor). For any $\tau \in (0,1)$, defined as follows:

[6] According to the regulations of the Sec. 199A final regulations taxpayers could claim a significant deduction of their income received in form of REIT dividends (Secs. 199A(a) and (b)(1)(B)).

$$\rho_{\text{quantile } \tau}(u_i) = \begin{cases} \tau u_i & \text{if } u_i \geq 0 \\ (\tau - 1)u_i & \text{if } u_i < 0 \end{cases} \quad (4)$$

where $u_i = y_i - x_i'\beta$. In Eqs. (3) and (4), the QR estimator is derived by minimizing the weighted sum of absolute errors, where the weights are dependent on the quantile.

Lastly, since herding is a time-varying phenomenon, we use the recently developed time-varying coefficient for the ordinary least squares (TV-OLS) regression developed by Casas et al. (2018). Unlike the rolling-window estimation, which results in loss of data and degrees of freedom, TV-OLS utilizes the entire sample period data set. The model is detailed below.

For a single equation, the TV-OLS can be largely estimated as

$$y_t = x_t^{\intercal}\beta(z_t) + u_t, \qquad t = 1, \ldots\ldots, T, \quad (5)$$

Where y_t is the dependent variable; $x_t = (x_{1t}, x_{2t}, \ldots., x_{dt})^{\intercal}$ and $\beta(z_t)$ are vectors of regressors and coefficient estimates, respectively, at time t. u_t represents the residuals satisfying $E(u_t|x_t) = 0$ and $E(u_t^2|x_t) = \sigma^2$

We use kernel smoothing (as opposed to splines and maximum likelihood estimation) to derive the time-varying coefficients. Casas et al. (2018) show that kernel smoothing techniques offer the advantage of handling dependency among variables and any form of error term distribution.

The smoothing variable, $z_t = \intercal = t/T \in (0,1)$, can be (i) a rescaled time variable, making the time-varying coefficient estimates be defined as unknown functions of time. That is, $\beta(z_t) = f(\intercal)$ or

(ii) a random variable, hence, the time-varying coefficients are defined as unknown functions of a random variable $\beta(z_t) = f(z_t)$.

We use the local linear (LL) Kernel method (as opposed to the local constant (LC) in our TVOLS estimations[7]. Casas et al. (2018) show that the LL estimator is asymptotically unbiased at the boundary, an advantage in the out-of-sample prediction. Under certain assumptions on kernel regularity, the size of the bandwidth, stationarity of x_t, z_t and u_t and error moments, these estimators are consistent and asymptotically normal.

[7] See Casas and Fernández-Casal (2022) for more details.

4. Empirical results

Table 3 presents the results of the OLS estimation for Eq. (1) for the various REIT sectors and the overall market, employing the total number of observations. In general, the behavior of investors with respect to correlated trading decisions is heterogeneous among the various sectors/subsectors. Herding behavior is captured by the coefficient of the squared term $CSAR^2$, namely β_2. According to the results presented, the coefficient on the non-linear term is significant and negative for the Lodging/Resorts sector, indicating herding of investors in this sector. According to Bohl et al. (2017), Demirer et al. (2019), and Aharon (2021), the true null hypothesis of no herding (anti-herding) is captured by a positive β_2, and the presence of herding should be captured by a negative β_2 coefficient, regardless of its statistical significance. Accordingly, herding is also evident for the Residential, Healthcare, Industrial, Office, Regional malls, and Shopping malls REIT sectors. For the Diversified, Freestanding, and Specialty REITs sectors, we detect the absence of herding.

Table 3: Estimation results of the OLS model

Subsector	β_0	β_1	β_2	Adjusted R^2
Residential	0.0048***	0.3550***	-0.3134	0.483
Diversified	0.0065***	0.8907***	1.0263	0.569
Freestanding	0.0049***	0.2851***	0.1083	0.289
Healthcare	0.0061***	0.2547***	-0.1947	0.230
Industrial	0.0047***	0.2908***	-0.0554	0.415
Lodging/Resorts	0.0078***	0.4790***	-0.2828***	0.432
Office	0.0048***	0.3172***	-0.1364	0.530
Regional malls	0.0033***	0.2820***	-0.2591	0.336
Self-storage	0.0047***	0.3205***	1.1280***	0.374
Shopping malls	0.0046***	0.3159***	-0.0175	0.535
Specialty	0.0076***	0.4884***	0.3958	0.380
All	0.0072***	0.4062***	0.2778	0.578

Note: *, ** and *** denote statistical significance at 10%, 5%, and 1%, respectively. The herding coefficient estimates are based on Eq. 1. $CSAD_{i,t} = \beta_0 + \beta_1 |R_{M,i,t}| + \beta_2 R^2_{M,i,t} + e_{i,t}$. To correct for autocorrelation and heteroskedasticity, we derive the results using a Newey-West (1987) consistent estimator.

Unlike the OLS regression, QR allows us to reach more robust inference regarding the existence of correlated trading behavior among REITs investors. QR reveals the relationship between the dependent variable and variables of interest across various points of its distribution and especially in the extreme areas where herding is more likely to occur (Zhou and Anderson, 2013). Moreover, in terms of the validity of the model, QR regression performs better when the dependent variable exhibits non-linearity, which is true for our CSAD measure.

Table 4 reports the estimated results of the QR. We observe a significant herding behavior as documented from the negative coefficient for the whole sample across the lowest CSAD values, namely, quantiles 2.5% and 5%. However, for the rest of the quantiles, a persistent anti-herding behavior is noticed, as reflected in a significantly positive herding coefficient. Turning our attention to results at the sector level, a herding effect is confirmed in all sectors in at least one of the lower tail quantiles (2.5th, 5th, 10^{th,} and 20th quantiles) of CSAD values. This suggests that when CSAD decreases, investors in the REIT sector ignore their private information and mimic the actions of other investors. The extremely low CSAD means sector returns mirror average market returns, resulting in diminished diversification benefits. The evidence of substantial herding behavior (negative and statistically significant β_2 in the upper 80th to 97.5th quantiles) in the Free-standing, Healthcare, Lodging, and Regional malls is consistent with the findings by Zhou and Anderson (2013), who document herding behavior in the US REITs in the upper quantiles of CSAD. Such observation can be attributed to large market price movements and volatile market conditions. Anti-herding at the upper quantiles when CSAD is diverging (investors are making independent investment decisions) is consistent with overconfidence, reduced uncertainty, and risk aversion.

Table 4: Herding coefficient estimate, β_2, based on quantile regression (QR)

Quantile	Residential	Diversified	Freestanding	Healthcare	Industrial	Lodging	Office	Regional	S-Storage	S. malls	Spec	All
0.025	-3.168***	-5.246***	-1.266***	-2.266***	-0.011	-1.963***	-1.531***	-0.105***	0.996***	-0.896***	-3.643***	-4.537***
0.050	-3.697***	-6.860***	-1.763***	-2.953***	-0.209***	-2.691***	-1.831***	-0.267***	0.631***	-1.087***	-4.136***	-4.221***
0.100	-0.166**	-0.794***	-0.667***	-0.043	-0.012	-0.497***	-0.592***	-0.336***	-0.237*	0.007	-0.128	0.203**
0.150	-0.214***	-0.098	-0.453***	0.156***	0.027	-0.096**	-0.210***	-0.096***	0.427***	0.334***	0.214**	0.705***
0.200	-0.003	0.166	-0.137***	0.256***	0.007	0.151***	-0.039	0.010	0.432***	0.337***	0.462***	0.882***
0.400	0.532***	2.310***	0.627***	0.140***	0.179***	0.000	-0.026	0.295***	1.471***	0.485***	0.982***	1.579***
0.500	0.885***	6.157***	0.509***	0.291***	0.316***	0.081*	0.410***	0.351***	2.126***	0.756***	0.956***	1.613***
0.600	0.826***	12.808***	0.532***	0.154**	0.492***	-0.083	0.318***	0.197***	2.254***	1.151***	0.993***	1.639***
0.800	0.922***	13.149***	0.204**	-0.419***	1.161***	-0.478***	0.263***	-0.684***	2.301***	1.897***	2.660***	1.734***
0.850	0.745***	12.614***	-0.017	-0.563***	1.049***	-0.536***	0.112	-1.206***	1.948***	2.289***	2.967***	1.999***
0.900	1.313***	12.250***	-0.434***	-0.765***	1.519***	-0.661***	0.345***	-1.311***	1.762***	1.778***	2.168***	1.283***
0.950	1.185***	10.889***	-0.017**	-1.397***	0.794***	-1.503***	0.074	-1.461***	2.011***	0.469***	5.906***	2.835***
0.975	1.784***	8.062***	-0.193*	-2.005***	0.176	-2.012***	-0.771**	-2.224***	-0.739	-1.402***	3.753***	1.741***

Note: the sample period is January 4, 1999 to December 8, 2023. *, ** and *** denote statistical significance at 10%, 5%, and 1%, respectively. S-storage and S. malls refer to Self-storage and Shopping malls, respectively. The herding coefficient estimates are based on equation 1. $CSAD_{i,t} = \beta_0 + \beta_1 |R_{M,i,t}| + \beta_2 R^2_{M,i,t} + e_{i,t}$.

Table 5: Descriptive statistics of time-varying Herding Coefficient Estimates ($\boldsymbol{\beta_2}$)

	Min.	Q1	Median	Mean	Q3	Max.	Bandwidth	Pseudo R^2
Residential	-43.625	-8.116	-2.571	-3.151	0.593	47.056	0.014	0.646
Diversified	-74.654	-1.817	6.927	7.087	15.631	45.215	0.028	0.777
Free-Standing	-14.230	-1.340	2.231	4.800	10.328	23.293	0.087	0.449
Healthcare	-18.921	-3.584	-0.433	0.915	3.936	34.825	0.014	0.634
Industrial	-25.747	-5.362	-2.412	-2.686	0.289	14.294	0.020	0.565
Lodge	-4.509	-0.990	0.176	3.177	5.481	23.201	0.099	0.578
Office	-19.148	-3.914	-0.967	-0.481	0.471	39.675	0.027	0.696
Regional mall	-48.584	-2.616	-0.025	0.795	2.846	31.523	0.018	0.635
Self-Storage	-5.919	-0.629	0.830	2.289	4.459	19.810	0.057	0.459
Shopping mall	-7.047	1.352	4.704	5.951	9.149	31.900	0.009	0.728
Specialized	-10.673	0.344	4.220	7.442	13.626	31.883	0.042	0.568
All	-7.743	-4.241	-0.744	-1.500	0.452	6.490	0.096	0.715

Note: the sample period is January 4, 1999 to December 8, 2023.

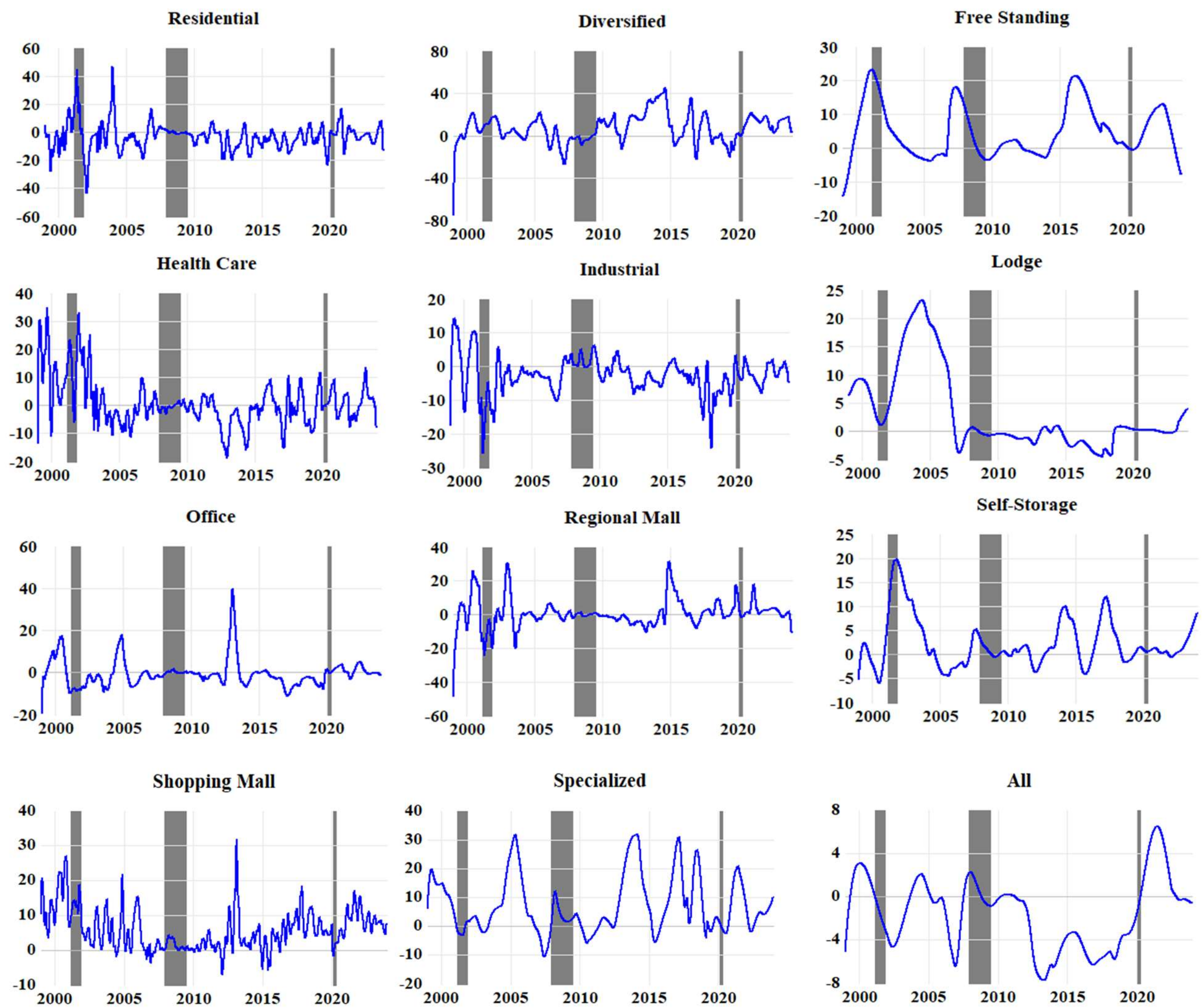
Table 5 presents the descriptive statistics of the time-varying herding coefficient estimates, β_2, the bandwidth and Pseudo R^2. The intensity of herding, shown by the minimum coefficient estimates, markedly varies across the sectors. Diversified (lodging) REIT sector with the lowest (highest) minimum β_2, of -74.65 (-4.51) had the most (least) intense herding on a specific day during the sample period. The third quartile and maximum coefficient estimates are all positive, signifying instances of intense and heterogeneous anti-herding behavior. REIT sectors switch between herding and anti-herding regimes over time. This conjecture is supported by Figure 3, which graphically illustrates the variations in herding (anti-herding) coefficient estimates. The three vertical grey bars represent the 2001 economic recession, the 2007-2009 global financial crisis (GFC), and the 2020 COVID-19-induced recession in the US, respectively.

The herding behavior of US equity REITs appears rather time-dependent, as revealed by Figure 3. We observe periods of significant herding for the whole sample (all sectors), with a mean value of the herding coefficient of approximately -7.74. Moreover, substantial herding is detected during the early period of the sample, that is, during 1999 and 2000, and continued with significant intensity around the 2001 US recession. Herding intensified before the global financial crisis, but cases of reduced anti-herding during the crisis period are observed. This window of substantial herding lasted until the COVID-19 pandemic which emerged in early 2020.[8] Finally, we observe

[8] We have replicated our herding analysis employing housing median sales price data for US Metropolitan Statistical Areas (MSAs) at a weekly frequency over the period of the 7th August 2010 to the 5th October 2024, based on data obtained from Zillows (https://www.zillow.com/research/data/). Results of the static model using OLS confirmed the absence of herding behavior (given a statistically significant (at the 1% level) positive β_2 coefficient of 21.58 over the

a phase from early 2020 when the coefficient turns positive, implying the presence of anti-herding behavior.

Figure 3: Time-varying herding Coefficient estimate ($\boldsymbol{\beta_2}$) based on Equation 1.



At the sector level, we unveil some interesting features of the returns' dispersion with respect to each sector's returns. Specifically, we observe a tendency of returns for Residential, Industrial, and Office REIT sectors to largely converge around sector returns after the 2001 recession, which is indicative of herding toward a sector-wide consensus. Those three sectors have the highest median

full sample, which, in turn aligns with the results in the REITs market. Next, we attempted to examine whether herding behavior exhibits a dynamic nature focusing around Covid-19. To this end, we employed a TVP model in estimating Equation (1) as we do in the REITs market, and herding is detected for the housing market between 23rd November 2019 and 31st July 2021.

(-2.57, -2.41, and -0.98, respectively) and mean (-3.151, -2.69, and -0.48, respectively) of the coefficient of interest β_2, indicating higher herding behavior relative to the other sectors.

4.1 Herding spillover analysis between sectors

Following a recent evidence showing significant return and volatility spillovers among US REIT sectors (see, Umar and Teplova, 2024[9]), it is natural to expect that the trading behavior of investors in one sector could transmit to another sector. Therefore, we set off to examine whether herding behavior in one sector is affected by events that take place in another sector, since spillover effects could explain the differences found in the two sectors. Galariotis et al. (2015) report that development in the US stock market exerts a significant effect on the formation of herding behavior in the UK market during the Asian and dotcom crisis. We adopt a process similar to that of Galariotis et al. (2015) to examine potential spillover effects in herding behavior across US REITs. For each sector, the following Eq. (6) is estimated using the squared returns of other sectors every time as a separate regressor. Herding spillover is revealed when coefficient β_3 is negative and statistically significant.

$$CSAD_{i,t} = \beta_0 + \beta_1 \left|CSAR_{i,t}\right| + \beta_2 CSAR_{i,t}^2 + \beta_3 CSAR_{j,t}^2 + e_{i,t} \tag{6}$$

For example, to test for spillover herding effects from the Lodging sector to the Residential (APMTS) sector, we estimate the following equation based on the above:

$$CSAD_{APMTS,t} = \beta_0 + \beta_1 \left|CSAR_{APMTS,t}\right| + \beta_2 CSAR_{APMTS,i,t}^2 + \beta_3 CSAR_{LODGING,t}^2 + e_{i,t} \tag{7}$$

The dependent variable of the equation is presented on the top left of the panel of Table 5. The results from Eq. (7) for the spillover effects from one sector to another are presented in Table 5. Similar to the previous analysis, the coefficient of interest here is β_3, which captures herding spillover effects from one sector to the other. For example, when estimating potential spillover effects from the Lodging sector to the Residential, we observe a positive and insignificant coefficient of 0.23. Furthermore, significant spillover-effects are observed for the Specialty sector

[9] Their results confirmed that US equity and mortgage REITs are susceptible to contagious spillovers during stressed market periods. The source of these contagious spillovers is Office REITs, which transmit the highest returns and volatility spillovers to the rest of the sectors. On a related front, Bahlous-Boldi et al. (2025) provide further evidence in favor of significant spillovers across US REIT sectors that vary with respect to economic policy uncertainty. In particular, retail, regional malls, and shopping centers act as shock transmitters, while self-storage, manufactured homes, and industrial REITs behave as net receivers.

originating from the following sectors: Healthcare, Free standing, Diversified and Shopping malls, whereas herding in Industrial sector is affected by the developments in various sectors such as Residential, Healthcare, Free standing, Office and Self storage with a negative β_3 coefficient of -0.65,-0.35, -0.14, -0.82 and -0.46, respectively, that is statistically significant at the 1% level. Herding in the Regional Malls sector appears to be affected by the events that take place in the Residential, Industrial, Office, and Self Storage sectors, with all these sectors exhibiting statistically significant negative β_3 coefficients. Significant negative coefficients are also reported for Free-standing, Residential, Industrial, Office, Regional malls, and Self-storage for the Healthcare sector. Finally, a striking result is revealed for the Diversified sector, where the developments in this particular sector appear to be affected by events that take place in all other sectors. Consistent with the findings of Umar and Teplova (2024) regarding return and volatility spillovers, the Office sector exerts a significant herding spillover effect across half of the REIT sectors examined. It is also noteworthy that the Industrial sector appears influential for half of the sectors, while the Residential/Residential sector follows with a significant effect in four cases out of a total of eleven sectors.

Table 5. Testing for spillover herding effects in the US REITs market

Residential	**β_3**	**Specialty**	**β_3**	**Industrial**	**β_3**	**Office**	**β_3**
Lodging	0.29	Residential	-0.13	Residential	-0.65***	Residential	0.16
Industrial	0.31	Lodging	-0.03	Lodging	0.12	Lodging	0.33
Healthcare	0.42	Industrial	0.07	Healthcare	-0.35***	Industrial	-0.10*
Free standing	0.64	Healthcare	-0.68***	Free standing	-0.14***	Healthcare	0.30
Diversified	0.16	Free standing	-0.40***	Diversified	-0.03	Free standing	0.39
Office	0.81	Diversified	-1.74***	Office	-0.82***	Diversified	0.46
Shopping malls	0.69	Office	0.14	Shopping malls	0.11	Shopping malls	0.55
Regional malls	0.95	Shopping malls	-0.27***	Regional Malls	0.20	Regional malls	0.18
Specialty	0.58	Regional malls	0.04	Specialty	-0.06	Specialty	0.17
Self storage	1.58	Self storage	0.54	Self storage	-0.46***	Self storage	0.21
Lodging	**β_3**	**Regional malls**	**β_3**	**Healthcare**	**β_3**	**Self storage**	**β_3**
Residential	1.46	Residential	-0.97***	Free standing	-0.23***	Residential	0.87
Industrial	0.72	Lodging	0.47	Residential	-1.32***	Lodging	0.11
Healthcare	0.61	Industrial	-0.49***	Lodging	0.33	Industrial	0.46
Free standing	0.58	Healthcare	0.37	Industrial	-0.28***	Healthcare	0.22
Diversified	0.18	Free standing	0.16	Diversified	0.31	Free standing	0.42
Office	0.89	Diversified	1.05	Office	-0.31***	Diversified	0.02
Shopping malls	1.03	Office	-0.78***	Shopping malls	0.03	Office	0.81
Regional malls	0.95	Shopping malls	0.56	Regional malls	-0.13**	Shopping malls	0.31
Specialty	0.48	Specialty	0.51	Specialty	0.34	Regional malls	0.48
Self storage	1.98	Self storage	-0.80***	Self storage	-0.64***	Specialty	0.18
Free standing	**β_3**	**Shopping malls**	**β_3**	**Diversified**	**β_3**		
Residential	-0.55***	Residential	0.82	Office	-0.63***		
Lodging	0.27	Lodging	0.09	Residential	-2.38***		
Industrial	-0.42***	Industrial	0.35	Lodging	-0.52***		
Healthcare	0.15	Healthcare	0.19	Industrial	-0.40***		

Diversified	0.85	Free standing	0.15	Healthcare	-2.44***
Office	-0.61***	Diversified	-0.13	Free standing	-1.62***
Shopping malls	-0.01	Office	0.58	Shopping malls	-1.42***
Regional malls	-0.16***	Regional malls	0.80	Regional malls	-0.69***
Specialty	0.53	Specialty	0.42	Specialty	-3.17***
Self storage	-0.69***	Self storage	1.39	Self storage	-1.65***

Note: *, ** and *** denote statistical significance at 10%,5% and 1% respectively.

A key driver of the spillover effects is the heterogeneous resilience of REIT sectors during economic downturns. For example, the demand for residential REITs (Residential) is largely inelastic during economic downturns since housing is an essential service. Similarly, the demand for nursing homes, senior living, medical offices, and hospital facilities is always generally rising. Since housing and healthcare are essential services, residential and healthcare REITs are more resilient than, for example, Industrial, shopping malls, and regional malls REITs. The Triple Net Leases (NNN), which require the tenant to enter long-term, lease contracts for industrial, office, and regional mall property leases and pay, in addition to the rent, real estate taxes, insurance, and maintenance costs, provide a stable stream of cash flows even during a downturn. The eruption of "big data" has resulted in an increasing demand for cloud computing and storage, digital infrastructure, and data center REITs. The promise of stable and predictable cash flow streams for residential, industrial, office, healthcare, specialty, and diversified sectors explains the significantly negative spillover coefficient estimates due to their hedging ability.

5. Conclusions

This paper examines first the herding behavior and then the spillover effects in herding behaviour in US REIT sectors. Employing a large sample of listed equity REITs spanning from January 4, 1999 through December 8, 2023, a battery of tests are used to cover static and dynamic herding behavior. Starting with the results of the baseline model, herding behavior is insignificant for the entire sample of REITs under the standard OLS estimator, with weak evidence of herding for the Lodging/Resorts sector. However, when examining herding via a more robust approach based on quantile regression, we document significant herding in the lowest CSAD values, namely, quantiles 2.5% and 5%, suggesting that herding behavior exhibits an asymmetric nature in US REITs. Further analysis based on a time-varying approach that accommodates the time-varying nature of the underlying relationship between series show that the formation of herding behavior for the whole market of US REITs occurs during various time windows, whereas at the sector level, the effect appears with tenuous evidence across two sectors. Importantly, our spillover analysis shows evidence of significant spillover effects in the herding phenomenon among the US REIT sectors. For example, the Office sector presents a significant herding spillover effect across half of the REIT sectors examined. Furthermore, Industrial sector appears influential for half of the sectors, while the Residential sector follows with a significant effect in four cases out of a total of eleven REIT sectors.

Our results could be useful for investment management purposes since herding can drive asset price volatility to a higher level and undermine the effects of portfolio diversification. Thus, investors should pay attention to sectors that are involved in significant herding spillovers for the sake of portfolio and risk management inferences in the US REIT sectors. Regulators should monitor the developments and deploy effective policies to mitigate the effects of herding since it is widely known that herding could ultimately pose a threat to market stability.

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