INTERNATIONAL REAL ESTATE REVIEW

2025 Vol. 28 No. 3: pp. 329 - 358

Herding in Investment Trusts: New Evidence Using Tick-by-Tick Data

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We study herding behaviour in Indian investment trusts, which comprise real estate investment trusts (REITs) and infrastructure investment trusts (InvITs), from July 2021 to March 2025. We employ two distinct methodologies: the high-frequency herding intensity statistic of Patterson and Sharma (2006), and a modified version of the return dispersion-based approach of Chang et al. (2000). The results provide clear evidence of herding in these markets, which is notable given that they have relatively less information asymmetry, volatility, and cash flow uncertainty than traditional equities. Noticeably, herding is absent before the reduction of the minimum trading lot size to one unit by the Indian regulatory body, the Securities and Exchange Board of India, in late 2021, which indicates the influence of increased retail participation. During COVID-19, herding was more pronounced in REITs than in InvITs, thus reflecting heightened uncertainty in the commercial real estate sector. These findings have broader implications for regulation, portfolio management, and market efficiency.

Keywords

Herding, Microstructure, REIT, InvITs, Investment trusts, India, Real estate investment trust

DOI: https://doi.org/10.53383/100406

1. Introduction

Herding is a phenomenon where the investors set aside their information or judgment and instead follow the other market participants [1]. Renowned economist John Maynard Keynes was one of the earliest to notice that people often disregard their information and follow the crowd (Keynes, 1964). He highlights the significance of social and psychological factors in the markets. The COVID-19 pandemic shows that wild swings in asset prices are not only due to the fundamentals of the assets. Sentiments and moods also impact asset prices.

The vast literature on herding in the financial markets states that herding depends on several factors, such as the market dynamics, behaviour of the participants, regulatory environment, and market structure, among others. Information asymmetry is unavoidable in financial markets, where some people possess superior information to others. Therefore, following others may be a rational decision. Devenow and Welch (1996) classify herding as either irrational or rational herding. They attribute human psychology to the former while noting principal-agent relationships and other externalities for the latter. However, ample evidence shows that herding increases volatility in the markets (Avramov et al., 2006; Froot et al., 1992; Shefrin, 2002; Wang, 1993).

The results of various studies on herding present mixed results. For instance, Christie and Huang (1995) do not find support for herding in the US equity markets. Similarly, Chang et al. (2000) find no empirical support for herding in developed markets such as the US and Hong Kong. However, they show that herding exists in emerging markets like South Korea and Taiwan. Demirer and Kutan (2006) do not find evidence for herding in the Chinese stock market. Kanojia et al. (2022) use an extensive daily, weekly, and monthly frequencies dataset and find no herding in the Indian equity markets. In contrast, Lao and Singh (2011) show that herding exists in both the Chinese and Indian markets.

Using intraday data, Gleason et al. (2004) note that herding does not exist in US exchange traded funds (ETFs). Similarly, herding in cryptocurrencies is studied extensively with mixed results (Bouri et al., 2019; Kaiser and Stöckl, 2020; Vidal-Tomás et al., 2019). Zhou and Anderson (2013) investigate herding in US real estate investment trusts (REITs) by using three decades of data and find evidence of herding in high quantiles of return dispersion. Similarly, Philippas et al. (2013) and Akinsomi et al. (2018) examine herding behaviour in the US and Turkish REITs. In a recent paper, Lesame et al. (2024) study herding in an international sample of 27 countries. The results show that herding in the international REIT market is driven by the developed economies, and the study period is from 2018 to 2021.

[1] Throughout history, we can see instances of herding, such as the Tulipmania in the Netherlands during the 1600s, South Sea Bubble of the 1720s in the UK, and the dot-com bubble during the dawn of the new millennium, among others.

In 2023, India became the most populous country in the world, and surpassed China (Livemint, 2023a). A year earlier, India had overtaken the UK to become the fifth-largest economy (Armstrong, 2022) globally. Despite the pandemic-induced lockdowns and resultant drop in the demand for commercial real estate space, the future of office spaces in India remains optimistic. Many Indians consider real estate an essential avenue for saving and investment. A recent study shows that ultra-high net-worth individuals in India allocate a quarter of their wealth to commercial real estate. Of these, 17% is in direct ownership form, 5% in REITs, and 3% in others (Livemint, 2023b). However, previous studies in the literature suggest that India has among the highest real estate prices in the world. According to the JLL and LaSalle transparency index, India is ranked 36th in real estate transparency (JLL, 2025). Regulatory and legal challenges make owning and maintaining real estate even more difficult. The rental yields from the residential properties are 3-5%, and the commercial real estate yields hover between 6 and 10%. All these make direct investment in real estate non-feasible for many Indians.

Currently, 4 REITs and 5 infrastructure investment trusts (InvITs) are listed on the National Stock Exchange (NSE). In April 2023, the NSE launched the Nifty REITs & InvITs index, the first-ever Indian index to track the performance of listed REITs and InvITs[2]. Since its first appearance in the USA in the 1960s, REITs have become a popular choice for many real estate investors. Similarly, a large number of master-business trusts/infrastructure trusts in the developed world hold cashflow-generating assets, the units of which trade on stock exchanges (Chen, 2022). InvITs are like master-business trusts/infrastructure trusts. While REITs own retail and commercial real estate assets, the scope of master-business trusts/infrastructure trusts is broader. They hold diverse assets like railroads, roadways, airports, port management, urban transport systems, and waste plants.

This study uses the term ‘investment trust’, which comprises REITs and InvITs. Investment trusts are a relatively new asset class in India. Therefore, we have limited literature on the theoretical and empirical aspects of investment trusts. Ananthanarayanan and Narla (2017) discuss the governance-related issues of Indian REITs, while Das and Thomas (2016) examine the opportunities and challenges ahead of Indian REITs. Shah and Bhagwat (2022) critically assess the Indian InvITs. Walia et al. (2023) show that Indian REITs perform better than bonds while having less volatility than equities, and at the same time, REITs enhance the performance of a diversified portfolio.

In this study, we investigate herding in Indian investment trusts. We use the herding intensity statistic of Patterson and Sharma (2006), which uses intraday transactions. In addition, we also use the most popular methodology of Chang et al. (2000), a dispersion of returns-based approach for herd detection. The empirical results support herding in Indian investment trusts. Interestingly, we

[2] https://www.niftyindices.com/Factsheet/Factsheet_REITs_InvITs.pdf

study the impact of the three following types of shocks on herding: 1) the global COVID-19 pandemic which had impacts on all walks of life, including the Indian REITs that appeared vulnerable due to their high exposure to office space market; 2) in the latter part of 2021, the Indian market regulatory body - the Securities and Exchange Board of India (SEBI), reduced minimum lot size to one unit, thereby encouraging more retail participation in investment trusts; and 3) the divestment of Embassy REIT by Blackstone. Our results are interesting; 1) REITs herd more than InvITs during the pandemic, 2) there has been an increase in herding after the lot size change, and 3) market activities like divestment have a negligible impact on investment trust herding.

To the best of our knowledge, this is the first study to investigate herding in Indian investment trusts. Also, we contribute to the literature on herding in REITs, with existing works primarily using lower frequency data, like daily data, whereas we examine the intraday dynamics of herding. Our results challenge the efficient market hypothesis (EMH) in an asset known for less volatility and information asymmetry while having high cash flow certainty.

The subsequent sections are as follows: Section 2 provides the motivations for the study. Section 3 describes the data and methodology. In Section 4, we discuss the results. Section 5 deals with robustness checks, and finally, Section 6 concludes our study.

2. Motivations for the study

While herding behaviour in equity markets has been widely studied, relatively limited attention has been given to such behaviour in alternative asset classes like REITs and InvITs, especially within emerging market contexts. Although relatively small compared to developed markets such as Europe and North America, these markets are nevertheless rapidly growing, thus providing avenues for portfolio diversification (Ooi et al., 2006).

Although investment trusts trade on stock exchanges, they differ fundamentally in terms of equities. Most equity returns are due to price change, while dividends constitute a minor portion of the total returns. Conversely, investment trusts distribute at least 90% of their net distributable cash flow. Therefore, the component of dividends in total returns is substantially high. The total return of Indian investment trusts is 10.47%, while the price return is a minuscule 2.26%[3].

Several features of investment trusts, such as high institutional ownership, restrictions on taking risky and unrelated activities, return of most of the free cash flow, and frequent capital raising from secondary markets, result in less

[3] These values are since the inception of the Nifty REITs & InvITs index (as of 30 April 2025).

information asymmetry than equities (Downs and Patterson, 2005; Jain et al., 2017; Jain and Upadhyay, 2021). Also, these entities have regular cash flow due to longer-term lease contracts. In addition, the value of the underlying asset is relatively straightforward compared to other more complex financial instruments. Therefore, investors can value these assets with relative ease.

As a result, Lu et al. (2014) note that there is hardly any difference between informed and uninformed investors in REIT markets. In such a case, herding in investment trusts should be negligible since there is broader agreement that herding is mainly due to the uncertainty of asset value arising out of information asymmetry, which does not appear to be severe in the case of investment trusts. Nevertheless, there is an overlap between the investor base of investment trusts and equities since investment trusts trade on stock exchanges. These structural features raise important questions about the relevance and manifestation of herding behaviour in such markets. Also, investment trusts are rarely mentioned by the business press and brokerage houses that provide buy-sell recommendations.

Gleason et al. (2004) note that modern financial markets are complex with information overload, and investors in these markets differ in their level of sophistication. Therefore, it is likely that less sophisticated investors would follow those who are more informed. As Glosten and Milgrom (1985) suggest, insiders and those with superior data access and processing are considered informed traders. Also, investment trusts are relatively new to India and have been around for less than a decade. Various studies note that behavioural biases, such as herding, are more of an emerging and frontier market phenomenon as opposed to the developed markets (Arjoon and Bhatnagar, 2017; Chang et al., 2000; Christie and Huang, 1995). Further, Arjoon and Bhatnagar (2017) emphasise that markets with low market capitalisation and trading volume, are in their infancy, and have informational bottlenecks are prone to herding. Although India has a relatively developed equity market, the same does not hold for REITs and InvITs. The size of Indian investment trust markets is small compared to developed economies like the US, Japan, or Singapore.

In a significant move to encourage retail participation in investment trusts, the Indian market regulatory body, SEBI, reduced the minimum subscription amount and lot size. This move has enabled individuals to trade and invest in investment trusts, thus increasing the volume and investor base. Nevertheless, this move has the potential to aggravate herding since several studies suggest retail investors are more prone to herding (Hsieh et al., 2020).

Being the most populous nation in the world and with nearly $41 trillion worth of real estate assets, India offers opportunities to both investment trusts and investors (Armstrong, 2022). However, an efficient market is necessary for further growth of this asset class. Behavioural biases like herding are contrary to the EMH of Fama (1970) and can hamper the growth of this sector in the long run. The finance and behavioural literature often attributes herding to market crashes and volatility. While informed traders incorporate private information into prices, herding can prevent them from trading as prices of the assets may deviate significantly from their intrinsic values for extended periods of time, thus leading to bubbles and market crashes.

The period of our study coincides with COVID-19 and other major geopolitical events such as the Russia-Ukraine war and Israel-Hamas tensions, among others. Since 2020, the Indian markets have experienced an explosion of trading due to the arrival of millions of new traders. Therefore, the post-COVID period witnessed a surge in retail trading activity, increased market volatility, and an initial public offering (IPO) boom. These conditions provide a natural laboratory to test behavioural hypotheses in a still-evolving market. Therefore, it is a period of uncertainty and wide intraday market swings. Like other asset classes, investment trusts saw increased trading activity in volume and number of transactions during this period of time. The extant literature shows that apart from being a distinct asset class, REITs have diversifiers, hedges, and safe-haven properties (Dimitriou et al., 2020; Hanif et al., 2024; Lee, 2010). So, many retail investors are exposed to REITs and InvITs either directly or through mutual fund units. The divestment of Embassy REIT in December 2023 by Blackstone, one of the world's largest asset managers, offers a unique shock event to assess how the market processes large-scale institutional exits. The study uses this event as a natural experiment to test whether correlated trading in other REITs and InvITs follows, which is indicative of herding behaviour or informational cascades.

Our study contributes to the behavioural finance literature by exploring whether herding behaviour can still emerge in an asset class characterised by transparent cash flows and relatively less information asymmetry. The study also adds to the growing literature on market efficiency in emerging financial markets, by testing whether shocks like COVID-19, regulatory changes like a change in minimum lot size, and significant institutional divestments trigger a herd-like situation in Indian REITs and InvITs.

In summary, the motivation for this study lies in the intersection of regulatory reforms, significant institutional divestments, and structural challenges faced by Indian investment trusts. The reduction of lot sizes by SEBI has expanded retail participation, while the exit of Blackstone from Embassy REIT signals evolving market dynamics. At the same time, the dependence of REITs on office space, especially post-pandemic, raises concerns about long-term viability. These developments underscore the need for a more in-depth examination of investor herding in such a relatively small yet rapidly growing dynamic market environment.

3. Data and Methodology

3.1 Data

We obtain the tick-by-tick data of listed investment trusts traded on the NSE from DataScope (Refinitiv)[4]. There are 9 investment trusts publicly traded on the NSE, which comprise 4 REITs and 5 InvITs. However, 3 of the 9 lack substantial data due to their recent listing. Therefore, we consider 6 investment trusts in this study, which are equally divided into 3 REITs and 3 InvITs. Notably, these 6 investment trusts account for 77.39% of the Nifty REITs & InvITs Index, a free float market capitalisation-based index designed to track the performance of investment trusts. Our data contain over 6.93 million transactions for the 6 investment trusts over a period of 44 months, from 01 July 2021 to 12 March 2025. We acquire closing prices of the investment trusts from the NSE website. The dataset contains 920 daily observations. Table 1 provides the descriptive statistics of the return series for each of the 6 investment trusts.

Table 1 Descriptive Statistics

REIT/InvIT	Industry	Return	Std Dev	Skewness	Kurtosis
Brookfield India REIT	Realty	8.36e-05	0.011	0.500	8.320
Embassy Office Parks REIT	Realty	4.42e-05	0.012	-0.320	7.310
India Grid InvIT	Power	5.71e-05	0.007	-0.340	6.890
IRB InvIT	Services	-3.06e-05	0.008	-0.911	11.700
Mindspace REIT	Realty	2.64e-04	0.010	0.166	6.830
Powergrid InvIT	Power	-4.36e-04	0.007	0.172	6.150

***Notes*:** The return series used in this study is calculated as the natural logarithm of the ratio of consecutive closing prices, i.e., $R_t = P_t/P_{t-1}$, where P_t denotes the closing price on day t. All closing prices are obtained from the NSE website. The full sample consists of 920 daily observations, which cover the period of 01 July 2021 to 12 March 2025.

We further divide our dataset into 2 sub-samples. The COVID-19 sub-sample is from 01 July 2021 to 23 February 2022. Throughout 2020 and 2021, most of the corporate sector worked from home (Yadav, 2020). A significant portion of the revenue for REITs comes from corporate office space leasing. We consider 24 February 2022 as the starting date for the post-COVID-19 era since the pandemic had subsided significantly, and this was also the day of the Russian invasion of Ukraine. While our baseline analysis utilises data from July 2021, we also consider data before this month for supplementary studies. These additional analyses focus on the impact of the COVID-19 pandemic and the minimum trading lot size reduction in August 2021. By examining these

[4] Although investment trusts also trade on the Bombay Stock Exchange (BSE), the NSE enjoys higher trading volumes.

periods, we aim to enhance our understanding of the herding behaviour in investment trusts and its potential correlations with significant market events.

3.2 Methodology

Studies on herding mainly use one of the following two approaches - (i) use of transaction data (Lakonishok et al., 1992; Patterson and Sharma, 2006), and (ii) use of return series (Chang et al., 2000; Christie and Huang, 1995).

3.2.1 Herding Intensity Measure

We use the intra-day herding intensity measure in Patterson and Sharma (2006) to investigate herding in investment trusts. This measure has several advantages over rival measures since it allows us to measure intraday herding with high-frequency transaction data. Many studies suggest that herding is an intraday phenomenon (Blasco et al., 2012; Henker et al., 2006; Zhou and Lai, 2009). Unlike some other herding measures, intraday herding does not assume herding only occurs during uncertain periods and extreme market conditions. In addition, this measure allows us to determine the level of herding for the entire market rather than a specific set of investors. Patterson and Sharma (2006) establish their herding measure with the support of the informational cascade model of Bikhchandani et al. (1992). According to Bikhchandani et al. (1992), information cascades form when investors make their decisions based on the actions of others while disregarding their information.

Patterson and Sharma (2006) note that if there is herding, buyer-initiated (up) and seller-initiated (down) runs would be longer than the case without the herding. If there is systemic herding by traders, then the herding intensity statistic would be negative and statistically significant[5].

The herding intensity statistic (H) for s run, investment trust j, on day t, is calculated as follows:

$$x_{(s,j,t)} = \frac{(r_s + 1/2) - np_s(1 - p_s)}{\sqrt{n}} \tag{1}$$

where r_s is the number of runs (sequences) for up, down, or zero trades, $1/2$ is the discontinuity adjustment factor, n is the total trades on day t for investment trust j and p_s[6] is the probability of a run type s.

Asymptotically, $x_{(s,j,t)}$ has a normal distribution with a mean of zero, and the variance is calculated as follows:

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[5] We classify the trades as up, down, and zero trades by using the tick-test according to which if the current price, P_t is higher than the previous price, P_{t-1}, then the trade is an up-tick (buyer-initiated). If $P_t < P_{t-1}$, then the trade is a down-tick (seller-initiated), and if $P_t = P_{t-1}$, the trade is a zero-tick (ambiguous on who initiated this trade).

[6] All three have equal probability of occurrence. Hence, the value is 0.33.

$$\sigma^2_{(s,j,t)} = p_s(1-p_s) - 3p_s^2(1-p_s)^2 \tag{2}$$

Finally, the herding intensity statistic is calculated as follows:

$$H_{(s,j,t)} = \frac{x_{(s,j,t)}}{\sqrt{\sigma^2_{(s,j,t)}}} \xrightarrow{a.d} N(0,1) \tag{3}$$

The herding intensity measure is increasingly used to investigate the intraday herding phenomenon. Espinosa-Méndez and Arias (2021) for Australian equity markets, Blasco et al. (2012) for Spanish equity markets, Vieira and Pereira (2015) for Portuguese equity markets, and Mandaci and Cagli (2022) for cryptocurrencies are among the several studies to use this measure.

While the herding intensity measures for each of the three types of runs—up (positive), down (negative), and zero (no price change), offer a detailed perspective on herding behaviour, there are benefits to consolidating these separate measures into a single daily value. This combined approach enhances the applicability of the analysis for multivariate studies, thus simplifying interpretation and allowing for a more holistic view of herding dynamics within the investment trusts. By utilising a singular value, researchers can more easily incorporate herding into broader regression models and statistical analyses, which facilitates a better examination of its impact alongside other variables. Therefore, we extend the herding intensity measure to a single metric that is run-type weighted as follows:

The run-weighted herding intensity measure $H_{rw,t}$ is defined as:

$$H_{rw,t} = \frac{r_p H_p + r_n H_n + r_z H_z}{r_p + r_n + r_z} \tag{4}$$

where $H_{rw,t}$ represents the overall herding intensity for day t, weighted by the number of runs in each category. Specifically, H_p, H_n, and H_z denote the herding intensity statistic for upward, downward, and zero-return runs, respectively. The terms r_p, r_n, and r_z represent the corresponding number of up, down, and zero runs observed on day t. This formulation allows for a consolidated herding indicator that reflects both the intensity and frequency of directional trading behaviour.

We further employ the following regression model to regress the run-weighted herding intensity statistic against firm-level factors such as turnover, market capitalization, and volatility to assess the tendency of investors to engage in herd behaviour. Our study period encompasses significant global events, including the COVID-19 pandemic, which profoundly affected various aspects of life, including the financial markets. We specifically examine whether the COVID-19 crisis played a significant role in influencing the herding behaviour. The pandemic introduced considerable uncertainty, and particularly affected sectors like commercial real estate. Although both REITs and InvITs have cash-generating underlying assets, the nature of these two subsets of investment trusts is vastly different. In the case of REITs, the underlying assets are income-generating commercial and retail real estate that are prone to vagaries of the broader economy and consumption. Indian REITs became even more vulnerable due to their over-reliance on commercial real estate, such as office space. However, the rapid adoption of work from home by the service industry seriously questioned the economic viability of REITs. In contrast, InvITs seemed less affected since these are involved in sectors like infrastructure, ports, highways, and power transmission, among others. As a result, we hypothesise that the onset of COVID-19 heightened herding behaviour in REITs due to increased information asymmetry and perceived risk.

In August 2021, SEBI reduced the minimum trading lot size to one unit and aligned the minimum application amount for REIT/InvIT IPOs with equity shares. This regulatory change likely enhanced retail investor participation, which potentially influenced herding behaviour across REITs and InvITs. In this study, we investigate whether a change in lot size had a meaningful impact on herd behaviour compared to the pre-lot size change period.

Next, we consider the divestment of Embassy REIT by global financial behemoth Blackstone in December 2023. The divestment of Embassy REIT serves as a market-specific shock. We test whether this event caused spillover effects, which led to increased herding in other investment trusts. For this, we consider an event window of (-5, +5) from the announcement date of 20 December 2023 (Day 0).

$$\begin{aligned} H_{rw,t} = \beta_0 + \beta_1 TO_t + \beta_2 MC_t + \beta_3 VOLAT_t + \beta_4 D_t^{REIT} + \beta_5 D_t^{COVID} \\ + \beta_6 D_t^{PreLotSize} + \beta_7 D_t^{Divest} + \beta_8 (D_t^{REIT} * D_t^{COVID}) + \varepsilon_t \end{aligned} \tag{5}$$

In Equation (5), the dependent variable $H_{rw,t}$ represents the run-weighted herding intensity on day t, which captures the combined influence of up, down, and zero trade runs. Among the independent variables, TO_t denotes turnover (a proxy for trading activity), MC_t refers to market capitalisation (firm size), and $VOLAT_t$ represents return volatility, which usually influences uncertainty-driven herding behaviour. In this study, we use the Garman-Klass volatility estimator to measure daily volatility (Garman and Klass, 1980). The dummy variable D_t^{REIT} indicates whether the stock is part of the REIT segment, while D_t^{COVID} captures trading during the COVID-19 period. $D_t^{PreLotSize}$ is a binary indicator for dates before the SEBI-imposed lot size change (before 11 August 2021). The interaction term $D_t^{REIT} * D_t^{COVID}$ assesses whether herding intensity in REIT stocks differed during the pandemic period.

3.2.2. Cross Sectional Absolute Deviation Approach

Christie and Huang (1995) realised that herding in the financial markets can be studied by using a simple yet intuitive measure called cross-sectional standard deviation (CSSD) or the dispersion of individual asset returns from market returns. Under extreme market conditions, the CSSD measure is smaller than expected if there is herding. As against this, rational asset pricing theories contend that individual asset returns have different sensitivities to the market return under extreme market conditions.

Chang et al. (2000) further develop the dispersion of the returns-based herding model. In this regard, they propose a less stringent version of the CSSD called cross-sectional absolute deviation (CSAD). The CSAD approach is based on the capital asset pricing model (CAPM), where the CSAD and the market return ($R_{m,t}$) have a linear relationship. Violation of linearity is when investors disregard their beliefs and information and follow the broader market.

The calculation of the CSAD is as follows:

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

where $R_{i,t}$ is the daily return of investment trust i on day t, and $R_{m,t}$ is the cross-sectional average return of N investment trusts on day t.

Chang et al. (2000) propose a quadratic equation to capture the herding as follows:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{7}$$

Interpretation of Regression Output:

H1: No herding, if γ_1>0 and γ_2=0
H2: Herding, if γ_2<0
H3: Anti-Herding, if γ_2>0

Over time, the CSAD approach has emerged as the leading workhorse for herding studies. For instance, Lam and Qiao (2015) in the Hong Kong markets, Caporale et al. (2008) in the Italian equity markets, Caporale et al. (2008) in the Greece markets, Tan et al. (2008) in the Chinese markets, and Vo and Phan (2017) in the Vietnamese markets, among others, use either the CSAD approach or its extension.

Wang and Hudson (2024) show that the standard, static CSAD-based regression model fails to detect herding due to the assumption that the CAPM is a perfect asset pricing model. When no herding exists, the CSAD approach will presume that CSAD and market returns follow the CAPM without considering its imperfections. The CSAD-based regression test hinges on understanding that a concave relationship exists between the CSAD and absolute market return. Nevertheless, Wang and Hudson (2024) show that despite the absence of herding, there is a convex relationship between these two. Hence, it is likely that the standard dispersion of returns-based tests shows no evidence of herding even if herding exists. They propose three solutions to overcome the limitations of the standard herding detection test[7].

[7] The third approach is based on considering large market movement for testing herding.

In the first approach, they set the intercept of the quadratic model to zero.

$$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t \tag{8}$$

A negative coefficient on the quadratic term (γ_3) indicates herding.

In the second approach, a new variable, symmetrical CSAD, is introduced, as follows:

$$SCSAD_t = CSAD_t, if R_{m,t} > 0$$
$$SCSAD_t = -CSAD_t, if R_{m,t} < 0$$

The following regression model is then estimated:

$$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \varepsilon_t \tag{9}$$

A negative coefficient on the cubic term (γ3) is interpreted as evidence of herding behaviour. All regressions are estimated by using Newey-West standard errors to correct for potential heteroskedasticity and autocorrelation in the residuals.

Since investment trusts trade on the stock exchanges along with equities, and there is an overlap between the traders who trade these instruments, there is the possibility of herding spillover from other assets to investment trusts and vice versa (Akinsomi et al., 2018; Galariotis et al., 2015; Yasir and Önder, 2023). To understand how the broader market, reality sector, and risk perception impact herding, we include Nifty 50 returns, the returns of the Nifty Realty Index, and India VIX[8] to the modified CSAD model (Equation 8). In addition, we also include the CSAD of the Nifty realty sector as a control for herding in the realty sector. Also similar to Equation 5, we add two indicator variables: i) a lot size change dummy for post lot size change, and ii) a divestment dummy that represents three months during the divestment of its entire stake in Embassy REIT by Blackstone. After this, we add the interaction of these two indicator variables with the quadratic term ($R_{m,t}^2$) to better explain for the post-lot change herding and the herding during the divestment event window. However, here we consider data from 17 May 2021, rather than the usual 01 July 2021, so we have more data points for the pre-lot-size period.

$$\begin{gathered} CSAD_t = \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \gamma_4 R_{Nifty50,t} \\ +\gamma_5 R_{Realty,t} + \gamma_6 VIX_t + \gamma_7 CSAD_{Realty,t} + \gamma_8 D_t^{LotSize} \\ +\gamma_9 \left(D_t^{LotSize} * R_{m,t}^2\right) + \beta_1 D_t^{Divest} + \beta_2 \left(D_t^{Divest} * R_{m,t}^2\right) + \varepsilon_t \end{gathered} \tag{10}$$

This approach considers a certain magnitude or examines a certain proportion of the set of market returns that are the largest in absolute magnitude. However, we disregard this approach for its arbitrariness in terms of the absolute value of the market return.

[8] India VIX is a volatility index based on the NIFTY Index Option prices.

4. Results and Discussion

In Table 2, we present the number of transactions and runs (sequences) for each up, down, and zero tick trade. Although zero tick trades (56%) are significantly higher than positive ticks (22%) and negative trades (23%), the percentage of positive (34%), negative (34%), and zero (32%) runs is nearly the same.

In Table 3, we provide the mean (median) herding intensity statistic for up, down, and zero runs. All values are negative. At first, we consider the mean of the herding intensity statistic for all 6 investment trusts for the full, COVID-19, and post-COVID samples. In the case of Embassy REIT, the herding intensity statistic values are negative and significant at the 10% significance level, thus suggesting weak herding for the up and down runs of the full sample and the down run of the post-COVID period. For the same REIT, H_p and H_n are negative but statistically insignificant during the COVID-19 pandemic. For all other investment trusts and periods, the herding intensity statistic is negative and statistically significant at least at the 5% significance level. Next, we consider the median values of the herding intensity statistic for all the investment trusts and three types of runs. The herding intensity statistic for the Embassy REIT is statistically insignificant for the up and down runs of the full, COVID-19, and post-COVID samples. The rest of the values are statistically significant, and at least at the 10% significance level. The consolidated daily value of run weighted herding intensity calculated with Equation (4) is negative and statistically significant at least at the 5% level of significance for all investment trusts and periods, irrespective of whether we consider the mean or median values.

Zhou and Lai (2009) show that herding is more pronounced during selling than buying. However, our results do not show bias towards herding on the selling side. For the mean (median) herd intensity measure, only 2 (4) of the 18 cases have down run values that are larger than the up run values. Interestingly, the herding intensity measure of REITs is consistently lower than that for InvITs. One plausible explanation could be that the InvITs are in areas such as highways and power, while REITs are in the commercial real estate sector. The quality of cash flows, assets, and risk differs between these two subsets of investment trusts.

Alhaj-Yaseen and Rao (2019) suggest that increased transparency has an inverse effect on the herding intensity in any market due to a fall in intentional non-informational herding. The markets for investment trusts have less information asymmetry than those of equities. In this regard, a comparison of the results of this study with other works that use the approach in Patterson and Sharma (2006) indicates that the intensity of herding in investment trusts is similar to that of the Australian equity markets (Espinosa- Méndez and Arias, 2021). As against this, we find the herding intensity of investment trusts is less than that of Spanish and Portuguese equities and cryptocurrencies (Blasco et al., 2012; Mandaci and Cagli, 2022; Vieira and Pereira, 2015).

Table 2 Total Transactions and Runs

REIT/InvIT	Total Trades	Positive Trades	Negative Trades	Zero Trades	Positive Runs	Negative Runs	Zero Runs
Brookfield India REIT	914,367	214,595	223,660	476,112	176,036	176,816	158,346
Embassy Office Parks REIT	2,082,639	534,891	549,397	998,351	439,283	440,206	378,056
India Grid InvIT	528,375	87,844	93,388	347,143	74,264	76,145	76,994
IRB InvIT	634,682	122,978	129,056	382,648	107,723	107,931	111,617
Mindspace REIT	1,057,928	255,631	263,775	538,522	209,026	209,650	188,348
Powergrid InvIT	1,711,543	289,979	311,585	1,109,979	259,284	265,245	259,992

***Notes*: The run-based herding measures are calculated by the author by using intraday tick-by-tick data sourced from Refinitiv Datascope.

Table 3 Herding Intensity Statistic

REIT/InvIT	H_p	H_n	H_z	H_{rw}
Panel A: Full Sample				
Brookfield India REIT	-3.152 (-2.463)	-3.064 (-2.357)	-5.003 (-3.957)	-3.584 (-2.644)
Embassy Office Parks REIT	-1.939 (-1.213)	-1.840 (-1.237)	-6.826 (-6.021)	-3.208 (-2.144)
India Grid InvIT	-5.488 (-3.965)	-5.210 (-3.538)	-5.047 (-3.272)	-5.149 (-3.353)
IRB InvIT	-4.493 (-3.456)	-4.416 (-3.359)	-3.877 (-2.784)	-4.163 (-2.989)
Mindspace REIT	-2.892 (-2.075)	-2.808 (-2.022)	-5.00 (-3.885)	-3.394 (-2.453)
Powergrid InvIT	-10.501 (-9.662)	-9.953 (-9.121)	-10.511 (-9.111)	-10.119 (-9.005)
Panel B: COVID-19				
Brookfield India REIT	-3.472 (-2.165)	-3.299 (-2.014)	-4.715 (-3.299)	-3.696 (-2.219)
Embassy Office Parks REIT	-1.082 (-0.748)	-1.621 (-1.045)	-5.887 (-4.651)	-2.521 (-1.766)
India Grid InvIT	-3.778 (-2.001)	-3.730 (-2.051)	-3.817 (-2.043)	-3.631 (-1.927)
IRB InvIT	-4.422 (-3.165)	-4.326 (-2.732)	-3.855 (-2.597)	-4.107 (-2.80)
Mindspace REIT	-3.467 (-2.201)	-3.300 (-2.173)	-4.563 (-3.466)	-3.638 (-2.437)
Powergrid InvIT	-5.703 (-4.260)	-7.612 (-6.040)	-6.714 (-5.904)	-6.484 (-4.916)

(*Continued…*)

(Table 3 Continued)

REIT/InvIT	H_p	H_n	H_z	H_{rw}
Panel C: Post-COVID-19				
Brookfield India REIT	-3.083 (-2.518)	-3.013 (-2.428)	-5.065 (-4.040)	-3.56 (-2.704)
Embassy Office Parks REIT	-2.124 (-1.402)	-1.888 (-1.264)	-7.028 (-6.252)	-3.356 (-2.254)
India Grid InvIT	-5.856 (-4.440)	-5.528 (-4.021)	-5.312 (-3.645)	-5.475 (-3.856)
IRB InvIT	-4.509 (-3.571)	-4.436 (-3.503)	-3.881 (-2.809)	-4.175 (-3.086)
Mindspace REIT	-2.768 (-2.072)	-2.703 (-1.954)	-5.090 (-4.030)	-3.341 (-2.462)
Powergrid InvIT	-11.534 (-11.219)	-10.457 (-10.038)	-11.329 (-9.884)	-10.902 (-10.009)

***Notes*:** This table reports the mean and median (in parentheses) of the herding intensity statistic for up (H_p), down (H_n), and zero (H_z) return runs. These statistics are calculated by using Equation (3). The sample period spans from July 2021 to March 2025. The run-weighted herding intensity statistic (H_{rw}) is calculated by using Equation (4). The critical values at the 10%, 5%, and 1% significance levels are -1.64, -1.96, and -2.56, respectively.

In 2021, the SEBI reduced the trading lot size to 1 unit of REIT/InvIT (The Hindu Businessline, 2021). Before this, the minimum trading lot size ranged from 100 to 2500 units (each REIT/InvIT had a different trading lot size). The reduction in trade size aimed to increase liquidity and encourage retail participation. A comparison of the trading volume and number of transactions shows that there has been an increase in trading post-reform[9].

In Table 4, we provide the herding intensity statistic for the 6 investment trusts before the implementation of lot size reduction to 1 unit of REIT/InvIT. The results indicate that herding is nearly absent for the up and down runs (except in the case of Powergrid InvIT), while herding exists for zero runs (except in the case of India Grid InvIT and IRB InvIT). A larger lot size prevents small investors from participating in this market. Therefore, it is plausible that large retailers and institutions, who are informed, did not herd in these markets. Our results support previous studies that show small retail traders herd significantly across financial markets and geographies (Barber et al., 2008; Chen et al., 2015; Rahman et al., 2015).

Table 4 Herding Intensity Statistic Prior to Reduction of Trading Lot Size

REIT/InvIT	obs.	H_p	H_n	H_z
Brookfield India REIT	119	0.411 (0.655)	0.385 (0.553)	-3.184 (-2.626)
Embassy Office Parks REIT	585	0.286 (0.519)	0.198 (0.373)	-4.900 (-4.572)
India Grid InvIT	604	-0.422 (-0.154)	-0.558 (-0.394)	-1.061 (-0.886)
IRB InvIT	604	0.006 (0.290)	-0.089 (0.164)	-1.009 (-0.877)
Mindspace REIT	252	-1.233 (-0.909)	-1.154 (-1.131)	-3.265 (-3.021)
Powergrid InvIT	62	-5.292 (-2.392)	-5.904 (-3.694)	-7.719 (-6.482)

***Notes*:** This table reports the mean and median (in parentheses) of the herding intensity statistic for up (H_p), down (H_n), and zero (H_z) return runs, calculated by using Equation (3). The minimum trade lot size was reduced to 1 on 11 August 2021; therefore, the end date for all investment trusts is 10 August 2021. The starting date varies depending on data availability and stock exchange listing. Specifically, the starting dates are as follows: India Grid InvIT and IRB InvIT - 01 March 2019; Embassy REIT - 01 April 2019; Mindspace REIT - 07 August 2020; Brookfield REIT - 16 February 2021; and Powergrid InvIT - 14 May 2021. Critical values for the test statistic are -1.64, -1.96, and -2.56 at the 10%, 5%, and 1% significance levels, respectively.

In Table 5, we provide the 4 ordinary least squares (OLS) regression results of run-weighted herding intensity on type of investment trust (REIT vs. InvIT) (Model 1); divestment of Embassy REIT (Model 2); COVID-19 and pre-lot-size change dummies (Model 3); and lastly, COVID-19 dummy, pre-lot-size

[9] Not reported in the paper.

change dummy and interaction of type of investment trust and COVID-19 pandemic (Model 4). In all 4 models, we control for turnover (TO_t), market cap (MC_t) and volatility ($VOLAT_t$)[10].

Table 5 Determinants of Intraday Herding

	Dep. Variable: Run Weighted Herding Intensity			
	(1)	(2)	(3)	(4)
β0	6.984	34.129***	10.271**	8.096*
	(1.137)	(4.706)	(2.384)	(1.856)
β1	-1.361***	-2.041***	-1.294***	-1.238***
	(-9.902)	(-11.975)	(-12.013)	(-11.564)
β2	0.387	-0.231	0.217	0.252
	(1.411)	(-0.759)	(1.138)	(1.315)
β3	60.331***	79.843***	47.515***	45.831***
	(4.095)	(4.519)	(5.663)	(5.61)
β4	3.212***	2.882***	2.895***	3.552***
	(8.295)	(7.512)	(8.983)	(9.634)
β5			0.481	1.563***
			(1.558)	(3.794)
β6			3.450***	3.471***
			(12.190)	(12.431)
β7		0.124		
		(0.113)		
β8				-2.215***
				(-5.513)
Obs.	5520	4600	6989	6989
Adj. R-square	0.089	0.119	0.145	0.151
F-Stat	136.5***	125.6***	198.0***	178.7***

Notes: The table presents OLS estimates of the run-weighted herding intensity ($H_{rw,t}$) regressed on trading activity and exogenous shocks. Models 1 and 2 use data from 01 July 2021 to 12 March 2025. In Model 2, Embassy REIT is excluded to isolate the herding response to the divestment event of Blackstone. The Divestment Dummy takes the value 1 during the event window (13 December 2023 to 28 December 2023), and 0 otherwise. For Models 3 and 4, the data end on 12 March 2025, but the start date varies depending on data availability. The REIT Dummy equals 1 for REIT stocks and 0 otherwise. The COVID Dummy equals 1 for the period of 11 March 2020 to 23 February 2022, which captures the effect of the pandemic. The $PreLotSize$ Dummy equals 1 before the regulatory change on 11 August 2021 and 0 thereafter. All regressions are estimated by using Newey-West standard errors to correct for potential heteroskedasticity and autocorrelation in the residuals. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. t-statistics are reported in the parentheses.

[10] Since our baseline model uses dataset that starts from July 2021, we exclude the interaction variable for COVID-19.

In Model 1, the coefficient of the REIT dummy (β_4) is positive and statistically significant, which suggest less herding in REITs than in InvITs. As a negative value of the herding intensity statistic suggests herding, a positive coefficient of the REIT dummy indicates that for REITs, the herding intensity statistic becomes more positive (conversely, less negative). In Model 2, we include the divestment dummy for Model 1, and the dataset excludes the Embassy REIT. We consider an event window of two weeks (-5,+5) for this purpose, and the coefficient of the divestment dummy (β_7) is positive and statistically insignificant. Thus, this suggests that the divestment of Embassy REIT by Blackstone had a negligible impact on the herding of other investment trusts[11]. In Model 3, we include the COVID-19 and pre-lot-size change dummy variables in Model 1. The coefficient of the COVID-19 dummy is positive but statistically insignificant, thus suggesting a negligible impact of the COVID pandemic on herding in investment trusts. The coefficient of the pre-lot-size dummy is positive and statistically significant, which imply more herding post reduction of the lot size to 1 in investment trusts. However, in contrast to Model 3, the coefficient of COVID-19 in Model 4 is positive and statistically significant. Nevertheless, both these models suggest that the COVID-19 pandemic did not aggravate herding in investment trusts. Model 4, a slight modification of Model 3, indicates that herding in REITs during COVID-19 significantly differed from that of InvITs during the same period of time. The negative and statistically significant coefficient of the interaction term suggests enhanced information asymmetry during the pandemic period, where the rapid adoption of work from home questioned the viability of REITs, as Indian REITs primarily cater to commercial real estate in terms of renting and leasing office space to corporate entities. As the herding literature suggests, this enhanced uncertainty would have made investors herd by following the decisions of others whom they deem more informed.

Next, we present the standard CSAD model regression (Equation 7) results in Table 6. The coefficients of the quadratic term ($R_{m,t}$) are positive and statistically insignificant for the full and the post-COVID sample, thus indicating no herding. The γ_2 is positive and significant for COVID-19, thus indicating anti-herding.

Nevertheless, Wang and Hudson (2024) show that the standard CSAD model is biased against detecting herding and propose three remedial measures as corrective action. We implement two of the modified models of Wang and Hudson (2024), the suppression of intercept (Equation 8) and the use of the symmetrical cross-sectional absolute deviation (SCSAD) instead of CSAD (Equation 9).

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[11] As a robustness measure, we consider a three-month window of both the pre and post divestment periods. The results are consistent with our main results.

Table 6 Herding in Indian Investment Trusts Using Standard Approach in Chang et al. (2000)

Variable	Full Sample	COVID-19	Post-COVID-19
α	0.004***	0.004***	0.004***
	(20.928)	(10.372)	(19.191)
γ_1	0.417***	-0.182	0.476***
	(5.039)	(-0.785)	(5.741)
γ_2	4.924	47.747**	2.423
	(0.774)	(2.120)	(0.399)
Obs.	920	163	757
Adj. R-square	0.275	0.167	0.301
F-stat.	175.40***	17.18***	163.40***

***Notes*:** This table presents the results of the regression of the CSAD, the cross-sectional absolute deviation, on the absolute value and square of the market return, $R_{m,t}$. The market return ($R_{m,t}$) is calculated as an equal-weighted measure. The full sample spans from July 2021 to March 2025. The COVID-19 period is defined from 01 July 2021 to 23 February 2022, and the post-COVID-19 period from 24 February 2022 to 12 March 2025. The cut-off date, 24 February 2022, corresponds to the onset of the Russian invasion of Ukraine. Standard errors are adjusted by using the Newey-West correction to account for heteroskedasticity and autocorrelation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. t-statistics are reported in the parentheses.

In Table 7, we provide the regression results of Equation (8), where we suppress the intercept term. Similarly, in Table 8, we document the results for the SCSAD-based regression model. In contrast to the results of a static model, the coefficients of the square term (γ_3) in Equation 8 and the cubic term (γ_3) in Equation 9 are negative and statistically significant at 1%, thus clearly suggesting herding in investment trust markets. Nevertheless, we should be cautious in interpreting the COVID-19 sub-sample results, as our dataset begins in July 2021, when nearly two waves of the pandemic had already passed.

Table 7 Regression without Intercept

Variable	Full Sample	COVID-19	Post-COVID
γ_1	0.006	-0.176***	0.024
	(0.215)	(-2.774)	(0.770)
γ_2	1.588***	2.252***	1.583***
	(23.472)	(14.030)	(26.010)
γ_3	-47.020***	-137.793***	-45.052***
	(-5.593)	(-6.109)	(-6.368)
Obs.	920	163	757
Adj. R-square	0.733	0.746	0.740
F-stat.	844.5***	160.9***	720.3***

***Notes*:** This table reports the results of the regression of the CSAD, the cross-sectional absolute deviation, on the market return ($R_{m,t}$), absolute value of the market return

($|R_{m,t}|$), and square of the market return ($R^2_{m,t}$). The market return is calculated by using an equal-weighted measure. Following the methodology in Wang and Hudson (2024), the intercept term is suppressed in the regression model. The full sample period spans from July 2021 to March 2025. The COVID-19 sub-period is defined as 01 July 2021 to 23 February 2022, and the post-COVID-19 sub-period as 24 February 2022 to 12 March 2025. The cut-off date, 24 February 2022, corresponds to the start of the Russian invasion of Ukraine. Standard errors are calculated by using a Newey-West estimator to correct for potential heteroskedasticity and autocorrelation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. t-statistics are reported in the parentheses.

Table 8 Regression Using SCSAD

Variable	Full Sample	COVID-19	Post-COVID
α	-0.0002	0.0006*	-0.0003*
	(-1.357)	(1.757)	(-1.818)
$\gamma 1$	1.306***	1.677***	1.319***
	(39.53)	(16.939)	(36.324)
$\gamma 2$	7.551**	-3.131***	9.477***
	(2.424)	(-3.059)	(2.949)
$\gamma 3$	-1344.900***	-7.644***	-1.371***
	(-7.303)	(-4.999)	(-8.351)
Obs.	920	163	757
Adj. R-Square	0.713	0.717	0.723
F-Stat	760.8***	138.0***	657.2***

***Notes*:** This table reports the regression results of the SCSAD on the equal-weighted market return and its higher-order terms. Following Wang and Hudson (2024), the symmetrical CSAD is defined as: $SCSAD_t$=$CSAD_t$ when $R_{m,t}$>0, and $SCSAD_t$=−$CSAD_t$ when $R_{m,t}$<0. The market return $R_{m,t}$ is calculated by using equal-weighted returns. The full sample period spans from July 2021 to March 2025. The COVID-19 sub-period is 01 July 2021 to 23 February 2022, and the post-COVID-19 sub-period is 24 February 2022 to 12 March 2025. The cut-off date, 24 February 2022, corresponds to the start of the Russian invasion of Ukraine. Standard errors are calculated by using a Newey-West estimator to correct for potential heteroskedasticity and autocorrelation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. t-statistics are reported in the parentheses.

In Table 9, we provide the results of Equation (10), an extension of the CSAD-based model without the intercept. While the coefficient of the Nifty 50 index returns is statistically insignificant, that of the realty index returns is positive and statistically significant. Also, the coefficient of the dispersion of the realty sector is positive and statistically significant (Model 2). A plausible explanation is that the investor groups who are trading these two assets are similar or the same. Our results suggest that broader market movement has little impact on herding in investment trusts. Meanwhile, the real estate sector equities still influence herding in investment trusts. Likewise, contrary to the equity markets where volatility exacerbates herding, the coefficient of the VIX series (also the coefficient of volatility in Table 5) suggests that volatility has the opposite impact of that in equities (Bharti and Kumar, 2022) and US REITs (Essa and Giouvris, 2025). The negative and statistically significant coefficient of the interaction variable ($D_t^{LotSize} * R_{m,t}^2$) suggests increased herding after the minimum lot size reduction, thus aligning with our results in Table 5. Like our results in Table 5, the coefficient of the interaction term ($D_t^{Divest} * R_{m,t}^2$) is insignificant, thereby suggesting that there is no herding due to the divestment of Embassy REIT by marquee investors like Blackstone Inc.

Table 9 Regression - Lot Size Change and Divestment

Variable	Model 1	Model 2
γ1	-0.036 (-1.471)	-0.037 (-1.580)
γ2	0.439*** (6.280)	0.507*** (8.725)
γ3	36.736** (2.254)	-0.999 (-0.270)
γ4	0.002 (0.113)	0.003 (0.219)
γ5	0.013* (1.915)	0.013** (2.030)
γ6	0.0001*** (4.923)	0.0002*** (12.707)
γ7	0.020 (1.491)	0.029* (1.869)
γ8	0.002*** (3.976)	
γ9	-33.100** (-2.264)	
β1		0.001 (1.577)
β2		10.941 (1.314)
Obs.	952	952
Adj. R-square	0.845	0.842
F-stat.	575.7***	562.6***

Notes: This table presents the regression of the cross-sectional absolute deviation of returns ($CSAD_t$) on market returns and control variables to detect herding. The control variables include: Nifty50 and realty-sector returns, VIX, and sectoral CSAD. $D^{LotSize}$ equals 1 after lot-size regulation (interacted to capture changes in herding), and D_t^{Divest} equals 1 during divestment periods (interacted similarly). All standard errors are Newey–West adjusted. The sample spans from 17 May 2021 to 12 March 2025. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. t-statistics are reported in the parentheses.

5. Robustness checks

While our study on herding in investment trusts suffers from a small sample size due to data availability, we ensure that our results are robust by performing additional tests and considering empirical and theoretical support from previous studies in the literature on herding. First, we consider an alternate version of our dependent variable in Equation (5), where instead of the run-weighted herding intensity statistic, we calculate the average daily herding intensity statistic and obtain almost the same results. For the CSAD-based approach, we replace the equal-weighted market return with market-cap-weighted market return, and our results are similar to those presented in Tables 6 to 9.

Next, we consider the realty sector stocks listed on the NSE. Since these are closest to investment trusts in terms of their business operations, and often, the investor pool is common to both of these asset classes, herding in these stocks validates our mainline results. For this, we consider the Nifty Realty Index[12], an index designed to reflect the performance of the realty sector. We calculate the run-based herding intensity statistic for up, down, and zero runs. The results suggest no herding for the up and down runs, while the herding intensity statistic for zero runs (Hz) suggests herding. The modified CSAD-based model suggests statistically significant herding during the post-COVID period[13]. Lastly, several studies related to herding behaviour in the Indian financial markets during the same period as ours suggest herding during and post-pandemic periods (Bharti and Kumar, 2022; Dhall and Singh, 2020).

6. Conclusions

Inspired by Patterson and Sharma (2006) and Chang et al. (2000), we examine herding in the Indian REITs and InvITs listed on the NSE. As the most populous nation and fourth largest economy, India is one of the important emerging real estate markets. Therefore, the efficiency of the market for investment trusts is the utmost requirement for domestic and global players to enter the Indian markets.

The results from using the run-based herding intensity statistic in Patterson and Sharma (2006) and dispersion-based regression approach in Chang et al. (2000) suggest herding in the secondary market for Indian investment trusts. Next, we explore how the following shocks impact herding in investment trusts: (1) COVID-19 (global pandemic); (2) minimum lot size change in 2021 (regulatory shock); and (3) divestment of Embassy REIT by Blackstone Inc. (market shock).

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[12] https://www.niftyindices.com/indices/equity/sectoral-indices/nifty-realty

[13] The results of all the robustness tests can be provided upon request.

Our results suggest that COVID-19 did not aggravate herding in investment trusts. However, during the pandemic, the REITs experienced more herding than InvITs due to increased uncertainty of the changing nature of corporate work. Next, the regulatory change of the reduction of the minimum lot size directly impacted herding in the subsequent post-lot-size change regime. Notably, both the run-based approach and dispersion of the returns-based approach indicate increased herding after the reduction of the minimum lot size. Our results are directly linked to enhanced retail participation, which was constrained earlier by a large minimum lot size. Lastly, the divestment of Embassy REIT suggests that such market activities had almost no impact on the herding.

Our results are interesting due to the unique nature of investment trusts. Investment trusts are less volatile than equities. Compared to other asset classes, the investors of these trusts face less information asymmetry due to various factors such as the dominance of institutional investors, stringent capital allocation requirements, and certainty of cash flows, among others. The present study is not devoid of limitations. As a result, one should be cautious before generalising our results to overall investment trusts. First, our dataset has a small number of investment trusts. In addition, the market for investment trusts in India has yet to mature. Therefore, future studies should include more markets with different levels of market maturity. Our results can differ when the market for investment trusts has more trusts available on the secondary markets. Nevertheless, we provide empirical evidence of herding and how the information environment can impact the former.

Acknowledgements

I am grateful to the editor, Tien Foo Sing, co-editor, Rose Neng Lai, and anonymous reviewer for their insightful comments and constructive suggestions, which have greatly improved this paper. Any remaining errors are mine alone.

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