The Lens of Green Focus:

Herding Behavior in the U.S. REITs Market

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This version: November 5, 2023

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ABSTRACT

Under the influence of growing media coverage, more investors are jumping into the green investment bandwagon, driven by the fear of missing out on opportunities aligned with shifting social preferences. This study examines investor herding behavior in the U.S. REITs market and its association with the growing awareness of sustainable investing. Using a time-varying cross-sectional absolute deviation (CSAD) model, we find that the herding effect varies over time, accumulating during slow market upturns, weakening during crises, and exhibiting some instances of anti-herding behavior. Our findings suggest that climate change concerns amplify the herding effect, while policy uncertainty diminishes it. Additionally, we observe a negative correlation between herding behavior and market volatility. The study explores the impact of volatility spikes in green assets on investor behavior, mitigating the herding effect and promoting positive social learning. These findings have policy implications and highlight the importance of green investment and climate concerns in advancing the sustainable development of REITs.

Keywords: Real estate investment trust, Green investment, Herding behavior, Climate change concerns, Uncertainty

Chapter 1 Introduction

The recognition of corporate social responsibility (CSR) has caused a shift in investment decisions, with increasing importance placed on Environmental, Social, and Governance (ESG) considerations. This shift has led to a rise in sustainable investing, attracting investors of all types, not just socially responsible ones. For instance, the U.S. Sustainable and Responsible Investment Foundation's report shows a significant 42% increase in assets under sustainable investing strategies, growing from $12.0 trillion in early 2018 to $17.1 trillion in early 2020. Similarly, MSCI 2021 Global Institutional Investor Survey indicates that more than 77% of investors expect a modest surge in ESG investments, with over 90% of institutional investors and pension funds expressing a willingness to engage in ESG investing.

Climate finance plays a critical role in sustainable finance, given its strong connection to climate change. Climate change represents one of the most pressing challenges facing society, with far-reaching implications for the well-being of individuals worldwide. Additionally, it poses significant systemic risks to the broader economy and financial system (Litterman et al., 2020). In the realm of climate finance, reducing greenhouse gas emissions takes center stage, as global financial institutions strive to achieve the goal of net-zero carbon emissions. The construction and building industry, identified as a major contributor to annual global CO_2 emissions, accounts for nearly 40% of energy-related emissions, as highlighted in the 2017 global status report on renewables.

REITs (Real Estate Investment Trusts) are widely recognized as valuable surrogates for studying the real estate market and serve as proxies for direct real estate investment (e.g., Lee and Chiang, 2010; Zhou and Lai, 2008). They have the potential to play a leading role in reducing carbon emissions and integrating ESG policies, aligning with the pursuit of net-zero carbon emissions, as emphasized by the National Association of Real Estate Investment Trusts (2022). Institutional investors such as Allianz Real Estate and BentallGreenOak have set ambitious targets to achieve net-zero emissions in their real estate portfolios. Additionally, Nuveen, a subsidiary of TIAA asset management, aims to achieve these objectives by 2040, surpassing the Paris Accord mandate by a decade. These developments underscore the ongoing revolution in climate finance within the real estate industry.

However, the conversation surrounding portfolio decarbonization poses challenges for investors in the U.S. REITs market. To navigate these challenges, investors must acquire the necessary skills to effectively respond to policy changes, adapt to market preferences, and manage uncertainties associated with green investments. These considerations have a direct impact on portfolio selection and performance, particularly in a market that is actively transitioning toward sustainability.

In response to the growing demand for sustainable investments, institutional investors in real estate and REITs markets have begun engaging with the Global Real Estate Sustainability Benchmark (GRESB). This participation enables them to align their strategies with the challenges posed by the sustainable investment boom. As illustrated in Figure 1, the number of institutions participating in GRESB has witnessed a significant surge, soaring from 539 in 2013 to 1,820 in 2022, representing an impressive 237% increase. This upward trend indicates that investors are actively adapting to the prevailing global trend of sustainable and climate-focused investments.

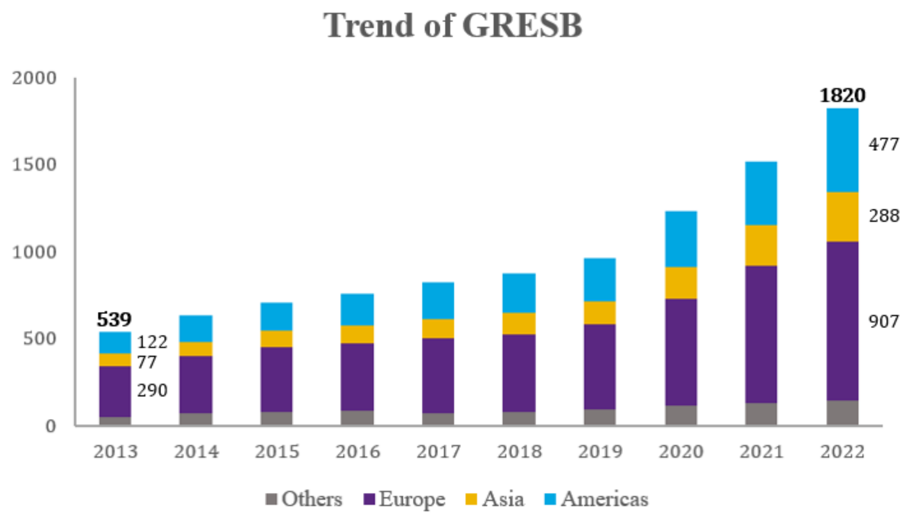


Figure 1 Number of investing institutions involved in GRESB

Note: The x-axis represents the year in the Gregorian calendar, and the y-axis represents the number of investing institutions participating in GRESB. The data is sourced from https://www.gresb.com/nl-en/2022-real-estate-results/

As previously mentioned, the growing green trend in the market, fueled by media coverage, is attracting an increasing number of investors who are jumping on the bandwagon to align with changing societal preferences (e.g., Bassen et al., 2019; Edmans, 2022). However, for investors in the REITs market, the process of transitioning towards sustainability and engaging in green investments can introduce potential uncertainties.

According to Dragomirescu-Gaina et al. (2021), these uncertainties can be categorized into two main groups. Firstly, in the process of green technological innovation, the rapidly changing government policies and regulations have a significant impact on the economic viability of emerging green technologies. Assessing and evaluating the risks associated with policy and regulatory changes becomes a crucial consideration for investors. Secondly, investors who are new to sustainability may require time to learn and adapt. Those seeking profitable and risk-adjusted investment opportunities in green technologies may encounter information barriers and increased costs associated with accessing relevant information. These factors add to the overall level of uncertainty for investors.

Taking inspiration from Chang et al. (2000), who established a connection between herding behavior and increased uncertainty, and acknowledging the potential consequences of the herding effect on asset prices and the risks of bubbles and crashes (Youssef, 2022), an important research question emerges regarding the impact of climate risk on financial stability through its influence on asset prices (Giglio et al., 2021). This motivated us to investigate the influence of the green investment boom in the REITs market on investor behavior and to examine whether the growing global concern about climate change acts as a potential driver for the herding effect.

Our study takes into account the sensitivity of coefficients in the static model to the choice of sample period (Stavroyiannis and Babalos et al., 2017). To address this, we follow a time-varying cross-sectional absolute deviation of asset returns (CSAD) model framework by Dragomirescu-Gaina et al. (2021) to examine investor herding behavior in the U.S. REITs market. Unlike previous studies suggesting a stronger herding effect in extreme market conditions (Zhou and Anderson, 2011), we offer an alternative perspective. Our research findings suggest that the herding effect accumulates during periods of slow market upturn, weakens during crises, and exhibits some instances of anti-herding behavior (Stavroyiannis and Babalos, 2017). This observation aligns with Hwang and Salmon (2004) findings during the Russian crisis, indicating that crises can act as turning points in restoring market equilibrium. Additionally, our study provides insights into the lack of significant herding effect observed in the U.S. REITs market during the subprime crisis (e.g., Philippas et al., 2013; Lin et al., 2018).

Furthermore, we examine the relationship between herding behavior and factors such as policy uncertainty and climate change in the U.S. REITs market, considering the impact of the ongoing green investment bandwagon. To measure climate change concerns, we utilize the Media Climate Change Concern Index (MCCC) developed by Ardia et al. (2022), which captures climate change-related news articles from prominent US sources. We also incorporate the Economic Policy Uncertainty Index (EPU) by Baker et al. (2016) as a measure of policy uncertainty. Our findings reveal that as concerns about climate change increase, the herding effect in the market becomes more pronounced, indicating a tendency for investors to blindly follow market consensus in the early stages of sustainability. However, as the EPU index rises, the herding effect diminishes, suggesting that investors demonstrate learning and adaptability in response to policy and regulatory changes, aligning with the conclusions of Huang et al. (2020).

Besides, our study investigates the relationship between uncertainty and herding behavior in the REITs market. Using the VAR framework and tools such as the Granger causality test and impulse response analysis, we find a negative correlation between herding behavior and market volatility, consistent with previous research in the U.S. equity markets (e.g., Litimi et al., 2016; BenSaïda, 2017). Following the VAR model setting introduced by Dragomirescu-Gaina et al. (2021), we incorporate the Dow Jones U.S. Select ESG REIT Index as a measure of green REITs. Significantly, our study reveals fascinating findings regarding the impact of green volatility shocks before and after the listing of the Dow Jones U.S. Select ESG REIT Index. We observe an amplification of the herding effect prior to the listing, followed by a weakening of the effect after the listing due to the influence of green volatility shocks. Based on these outcomes, we propose a potential hypothesis that as green investment progresses, herd behavior facilitates a process of social learning, contributing to a deeper understanding of sustainable investment principles and the mitigation of potential risks.

This paper contributes in three main ways: (1) It is the first study, to the best of our knowledge, to investigate herding behavior in the REITs market using a time-varying regression approach, revealing that the intensity of the herding effect varies over time; (2) This study adds to the current literature by exploring the relationship between the green investment bandwagon and herding behavior, an area that has received limited attention. The findings demonstrate that climate change concerns can serve as a driving force in intensifying herd behavior; (3) Additionally, the study discusses the potential impact of volatility spikes in green assets, which can redirect investor attention and facilitate positive social learning by mitigating the herding effect. These findings have policy implications and emphasize the importance of green investment and climate concerns in advancing the sustainable development of REITs, contributing to ongoing research in this field.

The remainder of this paper is organized as follows. The second section provides a literature review, outlining relevant studies in the field. The third section introduces the econometric methodology used in the analysis and presents the hypotheses. The fourth section presents the data used in the study, provides descriptive analysis, and discusses the empirical results. Finally, the fifth section concludes the paper and offers insights for future research extensions.

Chapter 2 Literature Review

2.1 Market-wide herding

Market-wide herding behavior is a subject of empirical study, arising from collective investor behavior influenced by a general market consensus. This behavior can lead to pricing errors and deviations from asset fundamental values. Chang et al. (2000) conducted a significant study in this area, proposing CSAD as a measure of market dispersion to assess the market herding effect in the stock market. CSAD is considered less sensitive to outliers compared to cross-sectional standard deviation of asset returns (CSSD) proposed by Christie and Huang (1995). A positive linear relationship between market returns and CSAD can be derived based on reasonable asset pricing modeling assumptions. If CSAD increases (decreases) with decreasing (rising) market returns, it indicates the presence of herding behavior in the market. Additionally, Hwang and Salmon (2004) also investigated herding using a modified model based on Christie and Huang (1995), specifically examining the cross-sectional dispersion of the factor sensitivities of assets in a given market.

2.2 Herding in REITs market

In the literature on herding behavior in the REITs market, several studies have contributed to our understanding. Zhou and Anderson (2011) conducted a study on E-REITs in the United States from 1980 to 2010 using quantile regression. They discovered that herding behavior in the REITs market is more prominent in high quantiles of return dispersion and is more likely to occur during market downturns. They also observed an asymmetry in herding behavior, with stronger herding during market declines. Philippas et al. (2013) analyzed herding behavior in the U.S. REITs market using data from January 2004 to November 2009. Their comprehensive analysis indicated that herding behavior is influenced by adverse macro shocks and deteriorating investor sentiment. However, they did not find evidence supporting the notion that financial crises exacerbate herding behavior. Lin et al. (2018) found that during the subprime mortgage crisis in 2008, continuous systemic recessions encouraged rational investment decisions among investors, leading to a lack of intensification in herding behavior in the U.S. REITs market during the financial crisis. This finding provides additional evidence on the relationship between market conditions and herd behavior.

On the other hand, Babalos et al. (2015) studied U.S. E-REITs data from January 2004 to June 2013 and did not find clear evidence of herding behavior when using a static CSAD herding model. However, their proposed regime-switching model revealed a significant herding effect during a defined crash regime, indicating that herding behavior may be contingent on specific market conditions. Furthermore, Huang et al. (2020) employed the Economic Policy Uncertainty Index (EPU) to gauge policy uncertainty. They discovered that U.S. REITs investors can adapt to the impacts of economic policy uncertainty and possesses the ability to mitigate the negative effects of herding.

2.3 Herding and ESG

The literature exploring the connection between environmental, social, and governance (ESG) factors and herding behavior is relatively limited. However, recent research has started to delve into this topic, focusing on the emergence of ESG in the financial market and its influence related to herding behavior. Gavrilakis and Floros (2023) investigated six European stock markets and discovered a connection between ESG and herding behavior in the Greek and French markets, offering limited evidence of ESG herding. Dragomirescu-Gaina et al. (2021) used a dynamic herding metric and found that investors' behavior in green asset allocations requires better information, while reducing policy-related uncertainty is crucial for portfolios with higher allocations towards greener assets. Przychodzen et al. (2016) discovered that mutual fund managers exhibit herding behavior in their investment decisions, which can be associated with motivations related to ESG strategies. Similarly, Benz et al. (2020) noted in their study that institutional investors, hedge funds, and portfolio advisors display herding behavior during the process of portfolio decarbonization. They also observed that mutual funds and hedge funds tend to imitate peers in ESG issues based on market returns, while pension funds and insurance companies invest in ESG to align with social norms and values. These studies provide valuable insights into the relationship between ESG investment and herding behavior in various contexts.

Chapter 3 Methodology and Hypothesis

Our herding analysis consists of three stages: (i) Initially, we use a static model based on the CSAD method by Chang et al. (2000) to detect herding behavior in the U.S. REITs market. We also introduce a dynamic framework to account for temporal changes in herding behavior. (ii) In the second stage, we examine the impact of policy changes and green investment opportunities on investor herding behavior in the U.S. REITs market, considering the growing concerns about climate change. (iii) Lastly, we investigate the relationship between herding behavior and conditional volatility of REITs market return using the vector autoregression (VAR) model, generalized impulse response functions (GIRFs), and Granger causality tests. We also explore the options available to REIT investors in response to heightened climate change attention, including allocation to general REITs or green REITs assets.

3.1 CSAD herding framework

The widely adopted method to detect market-wide herding behavior is based on static CSAD herding model (Chang et al., 2000), which uses CSAD as a metric to assess asset return dispersion. The calculation of CSAD is as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{3.1}$$

where $R_{i,t}$ represents the observed stock return of firm i at time t, $R_{m,t}$ is the cross-sectional average return of N assets at time t, and N denotes the number of REITs (firms) in the market, i.e., the number of assets being examined in the universe.

Chang et al. (2000) propose using Equation (3.2) to test for the herding effect. In the absence of herding, the equation shows a linear correlation with CSAD, resulting in a positive and statistically significant γ_1 coefficient. However, when herding is present, the relationship between CSAD and the square of market returns becomes nonlinear, indicated by negatively statistically significant γ_2 coefficients, signifying investors' tendency to follow the general market consensus rather than their own beliefs. A positively statistically significant γ_2 coefficient suggests anti-herding, where investors make decisions based on market fundamental information more rationally. CSAD can be viewed as a measure of the average proximity between individual REITs' returns and the average market returns. A lower CSAD suggests consensus among investors, focusing on a few specific stocks. Higher CSAD values indicate divergent views and differences in investment positions (Litimi et al., 2016).

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3.2}$$

Recent research has raised doubts about the static framework used in the method by Chang et al. (2000) due to limitations, such as sensitivity to sample period selection and unstable estimated coefficients (Stavroyiannis and Babalos, 2017). To address these concerns and gain a better understanding of herding changes over time, researchers have increasingly adopted dynamic methods (e.g., Stavroyiannis and Babalos, 2017; Dragomirescu-Gaina et al., 2021; Youssef, 2022).

Therefore, building on the model setting by Dragomirescu-Gaina et al. (2021), we adopt a dynamic framework that relaxes the assumption of constant coefficients in Equation (3.2). To estimate the model, we apply the Kalman filter in conjunction with the standard maximum likelihood estimation (MLE) approach. This methodology allows us to filter the time-varying γ_2, which captures the dynamic nature of herding behavior in the U.S. REITs market. By incorporating the time-varying property, we can better capture the changing nature of market mispricing over time, which aligns with the concept of the adaptive market hypothesis (Lo, 2004).

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_{2,t} R_{m,t}^2 + \varepsilon_t; \;\; \varepsilon_t \sim N(0, \sigma_v^2) \tag{3.3}$$

$$\gamma_{2,t} = \gamma_{2,t-1} + v_{2,t}; \;\; v_{2,t} \sim N\left(0, \sigma_{v_2}^2\right) \tag{3.4}$$

In the following sections, the filtered time-varying $\gamma_{2,t}$ as daily estimates of dynamic herding level parameters in the U.S. REITs market. These estimates capture the changing nonlinear relationship between CSAD and the square of market returns $R_{m,t}^2$.

Equation (3.3) represents a measurement equation that establishes a functional relation between the observed variables, $CSAD_t$, and the unobserved state variable $\gamma_{2,t}$. On the other hand, Equation (3.4) represents the state equation, which models the evolution of the unobserved state variable over time, following a Markov process.

As mentioned earlier in this section, we can state our first hypothesis.

H1. *Herding effect in the U.S. REITs market may changes over time.*

3.2 Detection of climate change herding

Under the influence and growing media coverage, an increasing number of investors have been drawn to join the bandwagon of green investing, driven by the fear of missing out on opportunities aligned with shifting social preferences (e.g., Bassen et al., 2019; Edmans, 2022). In our study, we aim to investigate whether the increasing focus on achieving net-zero carbon emissions in the U.S. REITs market, which has captured investor attention towards climate change issues, acts as a driver of herding behavior. To explore this relationship, we employ static and time-varying herding proxies.

In the static analysis, we modify the model following the approach of Gavrilakis and Floros (2023). We introduce the variable $MCCC_t$ as a proxy for climate change concern and redefine Equation (3.2) as follows:

$$CSAD_t = \gamma_0 + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^2 \cdot MCCC_t + \varepsilon_t \quad (3.5)$$

In our study, we utilize the variable $MCCC_t$ developed by Ardia et al. (2022) as a proxy for climate change concern. It quantifies media attention to climate change and allows us to capture the dynamic nature of climate change concerns. The MCCC index is based on climate change-related news articles from prominent U.S. newspapers and newswires and has been validated as an appropriate proxy variable in asset pricing analysis. Including it enables us to explore the impact of climate change concerns on herding behavior in the U.S. REITs market. To address pronounced fluctuations in the MCCC index, we applied a 30-day moving average as a smoothing technique, aligning with Ardia et al. (2022) for visualization purposes and creating a more stable series suitable for analysis. This serves as our preliminary validation model for climate change concerns and herding behavior. Our hypotheses are as follows:

H2a. *The coefficient γ_3 in Equation (3.5) is negative and statistically significant, indicating that climate change concern intensifies herding behavior in the U.S. REITs market.*

In our time-varying analysis, we adopt a similar approach to Youssef (2022) to investigate the determinants of herding behavior in the U.S. REITs market, focusing on the impact of climate change concerns. The real estate market is significantly influenced by government policies and regulations related to achieving net-zero carbon emissions, which introduce uncertainties regarding the economic viability of green technological innovations. To explore this, we examine the impact of policy uncertainty using the EPU index developed by Baker et al. (2016) on herding behavior in the U.S. REITs market. The EPU index is constructed from newspaper archives and covers various terms related to economics, uncertainty, legislation, deficit, regulation, and government entities.

Although a climate policy uncertainty index is available, its monthly frequency does not align with our daily data analysis, so we use the broader EPU index in our study.

In addition to the inclusion of climate change concerns and EPU variables, our analysis incorporates one of our control variables based on insights from Guney et al. (2017). This control variable is the squared daily market returns $\left(R_{m,t}^2\right)$, which serves as a measure of market volatility. Furthermore, building on the findings of Philippas et al. (2013), adverse macroeconomic shocks on REITs financing and deteriorating investor sentiment are identified as potential drivers of herding behavior in the U.S. market. To capture the influence of financing conditions and investor sentiment, we incorporate variables such as the percentage return $\left(R_{VIX,t}\right)$ of the CBOE Volatility Index and the change in 3-month LIBOR $(\Delta LIBOR_t)$ on day t in our regression analysis. Through empirical tests using Equation (3.6) and Equation (3.7), we aim to examine the impact of climate change concern and EPU on herding behavior, while taking into account other potential confounding factors:

$$herd_t = \beta_0 + \beta_1 MCCC_t + \beta_2 R_{m,t}^2 + \beta_3 R_{VIX,t} + \beta_4 \Delta LIBOR_t + \omega_t \qquad (3.6)$$

$$herd_t = \beta_0 + \beta_1 EPU_t + \beta_2 R_{m,t}^2 + \beta_3 R_{VIX,t} + \beta_4 \Delta LIBOR_t + \omega_t \qquad (3.7)$$

In Equation (3.6) and Equation (3.7), the variable $herd_t$ represents the level of herding in day t, which is estimated using the time-varying coefficient $\gamma_{2,t}$ obtained from Equations (3.3) and (3.4). The variable EPU_t refers to the EPU index at day t, which captures the level of economic policy uncertainty.

We incorporate the EPU variable along with MCCC to gain insights into how REITs investors respond to policy changes and increased climate change awareness, potentially affecting herding behavior in the U.S. REITs market. This analysis helps us understand the sources of uncertainty related to the green investing trend in the market, whether driven by government policy changes or higher information costs due to emerging green technologies. In light of these considerations, we present Equation (3.8) for further investigation:

$$\begin{gathered} herd_t = \beta_0 + \beta_1 MCCC_t + \beta_2 EPU_t + \beta_3 R_{m,t}^2 \\ + \beta_4 R_{VIX,t} + \beta_5 \Delta LIBOR_t + \omega_t \end{gathered} \qquad (3.8)$$

Huang et al. (2020) suggest that investors in the U.S. REITs market can adapt to policy uncertainties, potentially reducing herding behavior. Therefore, we anticipate that higher EPU may decrease the herding effect in the market. On the other hand, we expect that increased uncertainty related to climate change awareness may lead to higher information costs for investors, potentially amplifying herding behavior, which we term as "climate change herding". Based on the above expectations, we propose the following additional assumptions:

H2b. *The coefficient on the MCCC variable will be negative and statistically significant in Equation (3.6) ~ (3.8), indicating that the occurrence of "climate change herding" in the U.S. REITs market.*

H2c. *The coefficient on the EPU variable will be positive and statistically significant in Equation (3.6) ~ (3.8), suggesting that based on the learning ability of REITs investors, EPU has a mitigating effect on herding behavior in the U.S. REITs market.*

3.3 Examine herding and climate change-related uncertainty: a VAR approach

As highlighted by Chang et al. (2000), herding behavior in the U.S. REITs market is often linked to increased market uncertainty. In our previous section, we identified two potential sources of uncertainty related to the rise of green investing: changes in government policies affecting green technology innovations and investors' search for green investment opportunities leading to increased information costs. Previous studies have shown that volatility, as a measure of uncertainty, significantly impacts herding behavior. To investigate this relationship further, we estimate the GARCH(1,1) model to derive the conditional volatility of the U.S. REITs market and explore its association with herding behavior. The regression equation used for this analysis is as follows:

$$\begin{cases} R_{m,t} = c + \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{cases} \tag{3.9}$$

where c is a proxy for the average market return, and $\varepsilon_t \sim N(0, \sigma_t^2)$ are normally and identically distributed. The coefficients $\alpha_0,\ \alpha_1,\ \beta_1$ are restricted to be positive.

Existing research has predominantly focused on the relationship between herding behavior and return volatility in the stock market. Some studies have found a positive correlation between volatility and herding behavior (e.g., Blasco et al., 2012; Huang et al., 2015), while others have discovered a negative impact of market volatility on herding behavior (e.g., Holmes et al., 2013; Litimi et al., 2016; BenSaïda, 2017). However, there is limited discussion on the impact of herding on market volatility for REITs. To address this research gap, we investigate the relationship between herding and REITs' market volatility. Litimi et al. (2016) discovered that herding behavior can actually reduce overall market volatility by causing a focus on specific stocks and neglecting others.

According to the above discussion on the stock market, we expect that herding behavior can also be associated with uncertainty in the REITs market. To investigate this, we apply the VAR analysis, which include Granger causality test and GIRFs. Our analysis focuses on the herding proxy variable ($-\gamma_{2,t}$, derive from Equation (3.6) and (3.7)) as well as market condition volatility (σ_t, obtain from Equation (3.8)) and EPU (as a proxy for policy uncertainty, Baker et al. (2016)).

For a general VAR model, we consider a multivariate process $\{\boldsymbol{y_t}\}$ of dimension n. In an unrestricted VAR formulation, we specify the dynamics of $\{\boldsymbol{y_t}\}$ as follows:

$$\boldsymbol{B}(L)\boldsymbol{y_t} = u_t \tag{3.10}$$

where L is the lag operator, $\boldsymbol{B}$ is a polynomial matrix in the lag operator, $\boldsymbol{B}(0) = \boldsymbol{I_n}$ being the identity matrix, $E(u_t)$ represents the error term with a mean of 0, and $Var(u_t) = \boldsymbol{\Sigma}$ is the variance-covariance matrix with dimensions $n \times n$. In our specific application, where $n = 3$, we define the endogenous vector:

$$\boldsymbol{y_t} = \left[-\gamma_{2,t}, \sigma_t, EPU_t\right]' \tag{3.11}$$

It is important to note that for clarity in explanation, we multiplied all dynamic herding proxy $\gamma_{2,t}$ values used in the GIRF analysis by a negative sign. Thus, an increase in the value of $-\gamma_{2,t}$ indicates a rise in herding behavior in the market, rather than a decrease.

And the Granger causality equation can be stated as Equation (3.11):

$$\boldsymbol{y_t} = \boldsymbol{a} + \sum_{i=1}^{p} \boldsymbol{B_i}\boldsymbol{y_{t-i}} + \varepsilon_t \tag{3.12}$$

where $\boldsymbol{a}$ is a constant vector of offsets representing a restoring force to market equilibrium, and $\boldsymbol{B_i}$ is a 3×3 autoregressive matrix for each variable. In our analysis, we choose the lag $p = 1$ for practical considerations.

In order to better understand the mutual influence between variables, we also conduct GIRFs, which capture the response of the expected values of $\boldsymbol{y_t}$ at horizon $t + h$ to a one standard deviation shock at time t.

Our research seek to further investigate the impact of climate change-related uncertainties on herding behavior in the REITs market. We analyze how investors respond to policy and regulatory changes affecting green investments and how they navigate the challenges of identifying optimal opportunities with higher information costs. We hypothesize that these uncertainties are associated with herding behavior among investors. To achieve this, we extend our VAR analysis, drawing inspiration from the framework proposed by Dragomirescu-Gaina et al. (2021). The augmented endogenous vector is denoted as follows:

$$\begin{aligned}\boldsymbol{y_t} &= [-\gamma_{2,t}, General\ information_t, Asset - specific\ information_t]' \\ &= [-\gamma_{2,t}, EPU_t, VIX_t, \sigma_t^{Market}, \sigma_t^{Green}]'\end{aligned} \tag{3.13}$$

In our extended VAR model, we consider two types of information: general information (represented by proxies like EPU_t and VIX_t) and asset-specific information (measured by σ_t^{Market} and σ_t^{Green}, representing the volatility of the overall market and green REITs, respectively). This approach allows us to comprehensively analyze all sources of uncertainty affecting herding behavior within the VAR framework. By including the asset-specific component, particularly the volatility of green REITs, we can better capture the uncertainty related to investors' pursuit of green investment opportunities. This framework enables us to identify two distinct investment strategies among investors in the REITs market: one focusing on REITs without specific emphasis on green assets, and another specifically targeting green REITs assets.

We use the GARCH (1,1) model to estimate the daily return volatility of the Dow Jones U.S. Select ESG REIT Index. This index is weighted based on GRESB scores, which assess criteria like energy usage, water usage, carbon emissions, and leasable area covered by green building certifications, providing a robust sustainability analysis for individual REITs. The Dow Jones U.S. Select ESG REIT Index is specifically designed to target ESG-performing REITs, making it an ideal choice for our analysis to measure green REITs due to its comprehensive sustainability assessment and specific focus on real estate ESG.

Based on the discussion in this paragraph, we can conclude that the final assumption of this article is as follows:

H3. *We anticipate that the uncertainty arising from the green investment bandwagon in the U.S. REITs market will impact investor behavior, particularly in terms of social learning, and ultimately be associated with investor herding behavior.*

Chapter 4 Data and Empirical Results

4.1 Data and descriptive statistics

The data used in this study include the daily returns of the U.S. REITs listed on the New York Stock Exchange, American Express, and NASDAQ. The data cover the period from 2004 to 2022. The daily returns for each REIT are calculated using the price data obtained from the Zimen REITs database provided by CRSP (Center for Securities Price Research at the University of Chicago, USA). The CSAD measure, as defined in Equation (3.1), requires the market portfolio return $(R_{m,t})$ value. In line with previous literature, we use the equally weighted average of REIT returns as a proxy for the market portfolio returns $(R_{m,t})$. Descriptive statistics for the CSAD mertircs and market returns are presented in Table 1. The daily data consists of 4783 observations, and the number of equity REITs in the dataset ranges from 96 to 164 on any given trading day.

For the remaining data, we utilized the EPU index developed by Baker et al. (2016) as a reliable measure of policy uncertainty, capturing the level of uncertainty surrounding economic policies and regulations. For measuring climate change concerns, we employed the MCCC index by Ardia et al. (2022), specifically in the “Aggregate” category, which quantifies media attention to climate change and reflects public awareness. To address significant fluctuations in the MCCC index, we applied a 30-day moving average. Ardia et al. (2022) also used a 30-day moving average for visualization purposes, eliminating short-term variations and providing a more stable series for analysis.

However, in March 2023, when we retrieved the MCCC index data, it was only available up until June 2018. Hence, all empirical analyses conducted in Chapter 3.2 used data up to June 2018 as the last data point. Following the research timeframe of Gavrilakis and Floros (2023) in their analysis of ESG herding, the starting point of our data in Chapter 3.2 is set to April 2010. However, it's important to note that certain variables, such as the percentage return rate of VIX(R_{VIX}) for measuring investor sentiment and the 3-month LIBOR to assess the funding condition of REITs, are only included in the analysis for the period between April 2010 and June 2018, aligning with our research objectives. You can also find the descriptive statistics for these variables in Table 1.

In the empirical analysis conducted in Chapter 3.3, we follow the setup of Dragomirescu-Gaina et al. (2021) by considering both EPU and VIX as natural logarithms in our study. Therefore, in the entire study period part of Table 1, we present the descriptive statistics of EPU and VIX as $\ln(EPU)$ and $\ln(VIX)$ respectively. The economic and financial variables utilized in this study, including VIX and the 3-month LIBOR, were sourced from Bloomberg. Similarly, the Dow Jones U.S. Select ESG REIT Index, used as a measure of green REITs, was available from Bloomberg. Lastly, all the data in this study were combined based on the dates when the REITs were traded.

Table 1 Descriptive statistics

Data used throughout the entire study period: 2004/1 ~ 2022/12				
	$CSAD$	$R_{m,t}(\%)$	$\ln(EPU)$	$\ln(VIX)$
Mean	0.009	-0.002	4.496	2.880
Median	0.007	-0.001	4.499	2.809
SD	0.006	0.018	0.661	0.374
Skewness	4.650	-1.004	-0.111	0.911
Kurtosis	37.324	22.217	3.408	3.861
Data for detecting climate change herding only: 2010/4 ~ 2018/6				
	MCCC MA(30)	$R_{VIX}(\%)$	$3 - Month$ $LIBOR(\%)$	
Mean	0.581	0.003	0.597	
Median	0.559	-0.005	0.333	
SD	0.161	0.083	0.514	
Skewness	0.943	2.448	1.896	
Kurtosis	1.336	22.364	3.029	

Note: The table is divided into two sections. The top half of the table provides descriptive statistics for the entire study period, while the bottom half focuses on the data specifically for the empirical analysis in Chapter 3.2, covering the period from April 2010 to June 2018. In the table, MCCC MA(30) represents the 30-day moving average of the MCCC index, and R_{VIX} denotes the daily percentage return rate of VIX. All data are combined based on the dates when REITs were traded. The term SD refers to the standard deviation.

4.2 Empirical results

4.2.1 CSAD herding framework

Under the framework of the static CSAD model, we conduct a preliminary test using the Equation (3.2) model to determine the presence of herding behavior in the REITs market. Additionally, we performed empirical tests on four different panels to compare with previous literature on the U.S. REITs herding behavior. These panels include: (1) the period from January 2004 to November 9, 2009, as referenced in Philippas et al. (2013); (2) the period from January 2004 to June 2013, as referenced in Babalos et al. (2015); (3) the period from January 2004 to December 2014, as referenced in Huang et al. (2020);

and (4) the entire data range for our study, from January 2004 to December 2022.

Table 2 Estimates of herding behavior in the U.S. REITs market, static framework

$CSAD_t = \gamma_0 + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 R_{m,t}^2 + \varepsilon_t$				
Panel A: January, 2004 to November 9, 2009 (Philippas et al., 2013)				
	Constant	$\lvert R_{m,t} \rvert$	$R_{m,t}^2$	$Adj. R^2$
All equity REITs	0.006 (25.550)***	0.392 (14.303)***	-0.692 (-3.182)***	0.687
Panel B: January, 2004 to June, 2013 (Babalos et al., 2015)				
	Constant	$\lvert R_{m,t} \rvert$	$R_{m,t}^2$	$Adj. R^2$
All equity REITs	0.006 (30.035)***	0.323 (11.356)***	-0.155 (-0.593)	0.655
Panel C: January, 2004 to December, 2014 (Huang et al., 2020)				
	Constant	$\lvert R_{m,t} \rvert$	$R_{m,t}^2$	$Adj. R^2$
All equity REITs	0.005 (31.564)***	0.323 (11.600)***	-0.136 (-0.526)	0.657
Panel D: January, 2004 to December, 2022 (Entire data range for our study)				
	Constant	$\lvert R_{m,t} \rvert$	$R_{m,t}^2$	$Adj. R^2$
All equity REITs	0.006 (37.894)***	0.312 (12.911)***	0.027 (0.122)	0.599

Note: The table provides estimates for the equation $CSAD_t = \gamma_0 + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 R_{m,t}^2 + \varepsilon_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns from the corresponding market portfolio return, denoted as $R_{m,t}$. The estimations are conducted using ordinary least squares (OLS) with Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors, corresponding t-Statistics are given in parentheses. The adjusted coefficient of determination ($Adj. R^2$) is reported as a measure of model fit. Panel A presents the estimated coefficients for the period from January 2004 to November 9, 2009, as referenced in Philippas et al. (2013). Panel B includes the corresponding estimates for the period from January 2004 to June 2013, as referenced in Babalos et al. (2015). Panel C covers the period from January 2004 to December 2014, as referenced in Huang et al. (2020). Finally, Panel D provides the estimates for the entire study period, from January 2004 to December 2022. * Represent significance at the 10% level. ** Represent significance at the 5% level. *** Represent significance at the 1% level.

Table 2 displays the results obtained from the estimation of the Equation (3.2) model under different panels, including all equity REITs, using daily frequency data. In Panel A, the findings align with Philippas et al. (2013), revealing that the CSAD of REITs returns increases at a decreasing rate as the market returns increase. The statistically significant coefficient γ_2 indicates the presence of herding behavior.

Moving to Panel B, we come up with the same result of Babalos et al. (2015), where the CSAD of REITs returns relative to the market returns increases with the absolute value of the market returns. However, the insignificant γ_2 suggests the absence of herd behavior. Notably, Stavroyiannis and Babalos (2017) highlight the sensitivity of the static CSAD model to the choice of sample period, potentially leading to contradicting results between Panel A and Panel B.

In Panel C, despite using weekly data in their analysis, we obtain the same outcome as Huang et al. (2020), with an insignificant γ_2 signifying no herding behavior in the market. Finally, Panel D encompasses the entire study period, and the static CSAD model also supports the absence of herding behavior based on the insignificant γ_2.

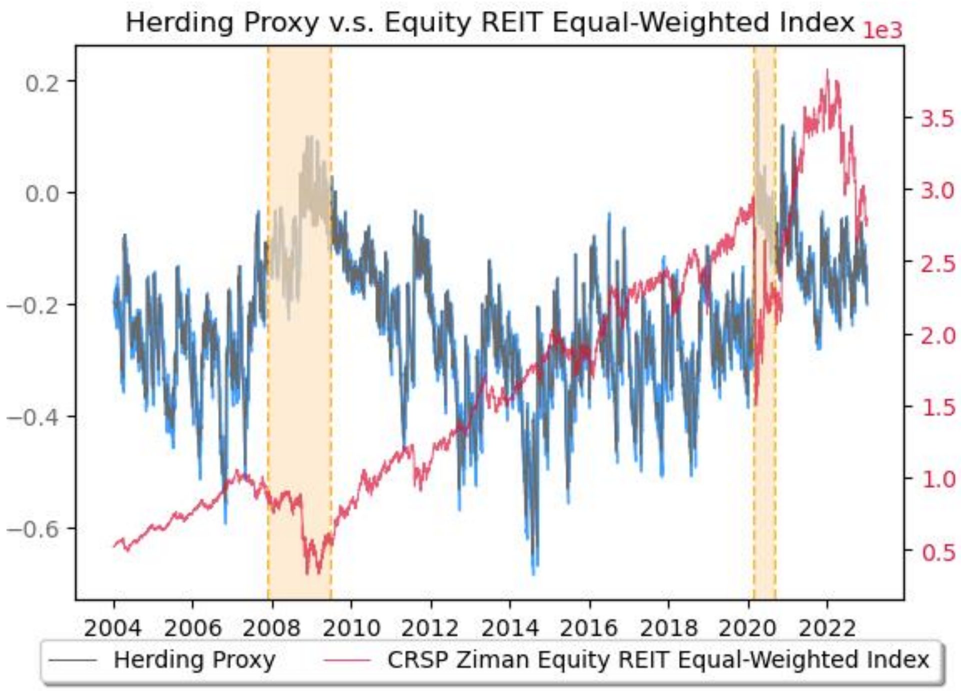


Figure 2 Dynamic herding metric and CRSP Ziman equity REIT equal weighted index

Note: The figure illustrates the estimated dynamic herding proxy, $\gamma_{2,t}$, with 95% confidence interval bounds (represented by the blue color). A statistically significant parameter is indicated when the upper and lower bounds of the confidence interval share the same sign. The figure also includes the CRSP Ziman equity REIT equal-weighted index, serving as a reference point for understanding the estimated herding proxy in relation to the overall performance of the REIT market.

To capture the dynamic nature of herding behavior, recent studies have shifted towards time-varying models. We adopt the framework proposed by Dragomirescu-Gaina et al. (2021), using a Kalman filter and maximum likelihood estimation to estimate the dynamic $\gamma_{2,t}$ in Equations (3.3) and (3.4). This approach enables us to comprehensively analyze herding effects over different time periods, addressing the limitations of static analyses and providing valuable insights into herding effect fluctuations and market responses.

Figure 2 presents the estimated dynamic herding proxy, $\gamma_{2,t}$, which captures the transition between herding and anti-herding behavior in the U.S. REIT market. This measure is not merely a statistical construct; it holds real market implications. We utilize the CRSP Ziman equity REIT equal-weighted index as a proxy for the REIT market price to aid interpretation. The herding proxy exhibits more negative values when the REIT market price rises slowly and overall market sentiment is positive, indicating a stronger herding effect. Conversely, during market downturns, the herding effect weakens, and in some cases, anti-herding behavior emerges. This pattern resembles the findings of Stavroyiannis and Babalos (2017) in the Islamic Market, where anti-herding tends to be more prominent during turbulent times. Moreover, this pattern aligns with the observations of Hwang and Salmon (2004) during the Russian crisis, suggesting that market crises or pressures can act as turning points in herd behavior and facilitate market equilibrium restoration. However, as the market recovers and enters a bull market phase, the herd effect gradually reappears, consistent with the adaptive efficient market hypothesis, which posits that mispricing may resurface over time.

To facilitate further exploration, we analyze the herding effect in the REITs market under abnormal market conditions by highlighting two significant events during our study period. In Figure 2, the orange-shaded area represents two major turbulent periods: (1) the global financial crisis, spanning from December 2007 to June 2009, as officially defined as the recession period by the NBER, and (2) the COVID-19 pandemic, specifically focusing on the first six months from March 11, 2020, to the end of August 2020, following the World Health Organization's (WHO) declaration of the outbreak as a global pandemic. We have selected a relatively short time period for COVID-19 due to the U.S. decision to implement early relaxation of social distancing restrictions and initiate measures to revive economic activity. During these turbulent periods, we observe that the impact of herding is relatively weak, and in some cases, anti-herding behavior is observed. These findings align with the research by Litimi et al. (2016), which suggests that the fuzzy market movements and divergent trading during the global financial crisis led to insignificant herding effects. Moreover, our observations further discuss the findings of Philippas et al. (2013) and Lin et al. (2018), who did not find pronounced herding behavior in the U.S. REITs market during the subprime crisis period.

The above explanation regarding the dynamic herding effect consistent with Hypothesis *H1*, which suggests that the herding in the U.S. REITs market can change over time. The observation of fluctuations and shifts in herding behavior supports the notion that herding effects are not persistent but can vary in response to different market conditions.

4.2.2 Detection of climate change herding

Green investing has become increasingly popular, attracting more investors as it aligns with societal preferences and receives extensive media coverage. Prior research by Gavrilakis and Floros (2023) suggests that ESG considerations can influence herding behavior in certain markets like France and Greece. In our study, we aim to investigate whether a similar trend is observed in the U.S. REITs market by examining the impact of climate change concerns on investor behavior, specifically focusing on herding and following market trends.

Table 3 Detection of climate change herding in the U.S. REITs market, static framework

$CSAD_t = \gamma_0 + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^2 \cdot MCCC_t + \varepsilon_t$					
	Constant	$\lvert R_{m,t} \rvert$	$R_{m,t}^2$	$R_{m,t}^2 \cdot MCCC_t$	$Adj. R^2$
All equity REITs	0.006 (72.047)***	0.158 (10.773)***	3.341 (5.735)***	-6.742 (-4.200)***	0.446

Note: The table provides estimates for the equation $CSAD_t = \gamma_0 + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^2 \cdot MCCC_t + \varepsilon_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns from the corresponding market portfolio return, denoted as $R_{m,t}$, MCCC represents the 30-day moving average of the MCCC index by Ardia (2022). The estimations are conducted using ordinary least squares (OLS) with Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors, corresponding t-Statistics are given in parentheses. The adjusted coefficient of determination ($Adj. R^2$) is reported as a measure of model fit. The sample period used is from April 2010 to June 2018. * Represent significance at the 10% level. ** Represent significance at the 5% level. *** Represent significance at the 1% level.

In the static analysis framework, we followed the methodology and study period used by Gavrilakis and Floros (2023), which spans from April 2010 to December 2020. However, due to the limited availability of our climate change concern measure, MCCC, up to June 2018, we restricted the data period from April 2010 to June 2018 to align with the available data. The results in Table 3 indicate a significant negative coefficient γ_3, indicating a negative relationship between an increase in MCCC and REIT return dispersion. This supports Hypothesis *H2a* of our study, indicating that as market concerns about climate change intensify, herding behavior becomes more prominent. This finding aligns with the observations of Benz et al. (2020), who identified herding behavior among investors, portfolio advisors, and hedge funds in the context of portfolio decarbonization.

Furthermore, we delve deeper into the determinants of herding behavior in the REITs market by incorporating the estimated time-varying herding effect coefficient, $\gamma_{2,t}$, as a measure of herding intensity at each time point, following a methodology similar to Youssef (2022). In particular, we aim to examine whether investors exhibit herding behavior in response to the market atmosphere characterized by heightened awareness of green investments. To address this question, we focus on the key variables of interest in our study $(MCCC \; and \; EPU)$, and their relationship with herding behavior. As mentioned above, the inclusion of the EPU variable is motivated by the understanding that government policies and regulations play a significant role in shaping investors' inclination towards green investments. The empirical analysis period corresponds to the timeframe presented in Table 3, taking into account the availability of MCCC data.

Table 4 Determinants of herding in the U.S. REITs market (Climate change herding)

	Equation (3.6)	*Equation (3.7)*	*Equation (3.8)*
	(1)	(2)	(3)
Intercept	-0.236	-0.453	-0.389
	(-12.789)***	(-13.380)***	(-9.156)***
$MCCC$	-0.100		-0.070
	(-3.537)***		(-2.484)**
EPU		0.036	0.030
		(4.764)***	(3.940)***
R_m^2	82.310	79.775	77.016
	(3.513)***	(3.302)***	(3.257)***
R_{VIX}	-0.064	-0.060	-0.056
	(-2.476)**	(-2.452)**	(-2.261)**
$\Delta LIBOR$	3.073	2.689	3.149
	(5.255)***	(4.668)***	(5.565)***
$Adj. R^2$	0.138	0.152	0.161

Note: The table presents the regression results of the model in Equation (3.6) to Equation (3.8), where MCCC represents the 30-day moving average of the MCCC index developed by Ardia (2022), EPU represents the natural logarithm value of the EPU index $(\ln(EPU))$ developed by Baker et al. (2016), and R_{VIX} denotes the daily percentage return rate of VIX. The estimations are conducted using ordinary least squares (OLS) with Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors, corresponding t-Statistics are given in parentheses. The adjusted coefficient of determination $(Adj. R^2)$ is reported as a measure of model fit. The sample period used is from April 2010 to June 2018. * Represent significance at the 10% level. ** Represent significance at the 5% level. *** Represent significance at the 1% level.

Table 4 presents the estimation results of the regression models specified from equations (3.6) through (3.8). Starting with the analysis of MCCC in equation (3.6), the negative and statistically significant coefficient of MCCC aligns with the findings from the static analysis in Table 3. This suggests that as market awareness of climate change increases, REITs investors are more likely to follow the bandwagon of green investment, disregarding their private information and engaging in herding behavior. Moving to the regression analysis of equation (3.7), the positive and statistically significant coefficient of EPU implies that investors in the REITs market exhibit some learning or immunity to the uncertainties arising from policy and regulatory changes. This reduced impact of herding behavior in response to EPU aligns with the findings of Huang et al. (2020) and provides further support to their results. Furthermore, in the regression analysis of equation (3.8), when both MCCC and EPU are considered, the results indicate that an increase in MCCC exacerbates herding behavior, while an increase in EPU reduces herding behavior in the market. These findings are in line with Hypothesis *H2b* and Hypothesis *H2c* proposed in this study.

These findings suggest evidence of "climate change herding" in the U.S. REITs market, where investors social preference swings and exhibit herding behavior in response to the growing focus on green investments. The uncertainty surrounding green investments may stem from various factors, including policy changes and heightened information costs. However, further causal analysis is needed before drawing definitive conclusions.

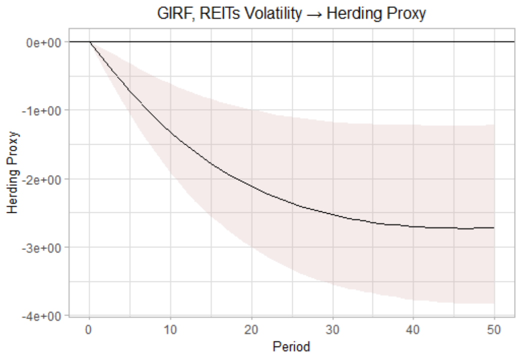
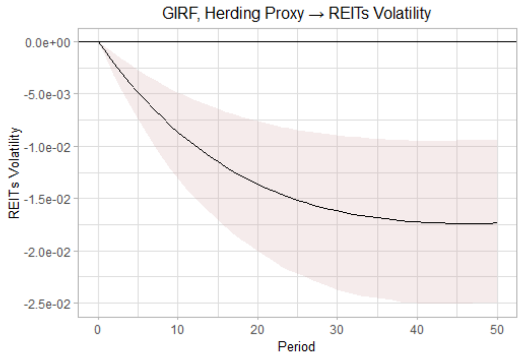
4.3.3 Examine herding and climate change-related uncertainty: a VAR approach

Table 5 Granger causality test result 1

Granger causality				
Direction of causality	*Number of lags*	*F-value*	*p-value*	*Decision*
REITs volatiolity →Herding proxy$(\gamma_{2,t})$	1	17.287	(3.27e-05)***	Yes
Herding proxy$(\gamma_{2,t})$ *→REITs volatiolity*	1	18.497	(1.74e-05)***	Yes
EPU →Herding proxy$(\gamma_{2,t})$	1	18.354	(1.87e-05)***	Yes
Herding proxy$(\gamma_{2,t})$ *→EPU*	1	190.94	(2.20e-16)***	Yes

Note: The variable $\gamma_{2,t}$ represents the dynamic herding proxy. REITs volatility is derived using the GARCH(1,1) model with the REITs market return. EPU represents the natural logarithm value of the EPU index $(\ln(EPU))$ developed by Baker et al. (2016). The analysis covers a sample period from January 2004 to December 2022. The numbers in parentheses indicate the p-value. * Represent significance at the 10% level. ** Represent significance at the 5% level. *** Represent significance at the 1% level.

In our previous empirical research, we discovered that the increasing awareness of green investing in the REITs market may influence investors and potentially impact herding behavior. This finding has motivated us to further investigate the relationship between herding behavior and uncertainty in the REITs market. To achieve this, we utilize market volatility and EPU as measures of market and policy uncertainty, respectively. By estimating VAR model with a multivariate system described in Equation (3.11), we aim to establish a clearer understanding of the relationship between herd behavior and volatility, as well as EPU. For this analysis, we use all available data intervals from January 2004 to December 2022 in our study.

Herding response to a generalized one SD shock in REITs conditional volatility	REITs conditional volatility response to a generalized one SD shock in Herding
	

Herding response to a generalized one SD shock in EPU

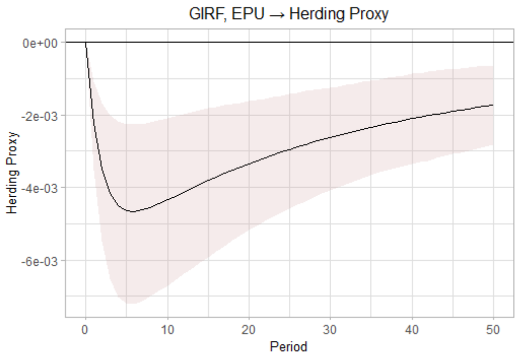


Figure 3 Responses between herding and uncertainty

Note: For ease of explanation, in this figure, the dynamic herding proxy is denoted as $-\gamma_{2,t}$, meaning it is multiplied by a negative sign. EPU represents the natural logarithm value of the EPU index $(\ln(EPU))$ developed by Baker et al. (2016). REITs volatility is derived using the GARCH(1,1) model with the REITs market return. The analysis covers a sample period from January 2004 to December 2022. The term SD refers to the standard deviation.

Table 5 presents the Granger causality test results for Equation (3.11). Our analysis reveals a dual Granger causality between the herding proxy $(\gamma_{2,t})$ and both market volatility and EPU. These findings suggest a bidirectional interaction between uncertainty and herding behavior. To further investigate the direction of these interactions, we employ the GIRFs. The GIRFs help us understand the expected average impact of shocks on the multivariate system described in Equation (3.11).

Notably, we multiplied all dynamic herding proxy $\gamma_{2,t}$ used in the GIRFs analysis by a negative sign for clarity. Thus, an increase in $-\gamma_{2,t}$ indicates a rise in herding behavior, not a decrease. Figure 3 reveals significant bidirectional interactions between herding behavior and REITs market volatility. Contrary to some previous literature suggesting that higher volatility drives more herding behavior, we find a negative relationship between herding and REITs market volatility. This indicates that herding tends to reduce overall market volatility, consistent with previous studies in the U.S. stock market (e.g., Litimi et al., 2016; BenSaïda, 2017). This phenomenon aligns with the insights of Hwang and Salmon (2004), where herding behavior has a positive impact on individual stock volatility but a negative impact on the average volatility of the overall market.

By the way, we find a decrease in herding behavior with positive EPU shocks, which supports previous finding in Table 4. Aligns with Huang et al. (2020), indicating that U.S. REIT investors exhibit adaptability and immunity to economic policy uncertainty.

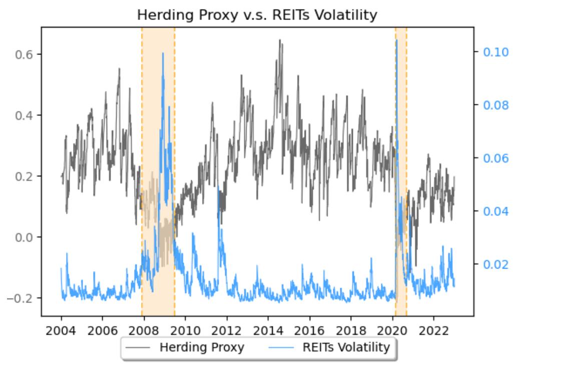
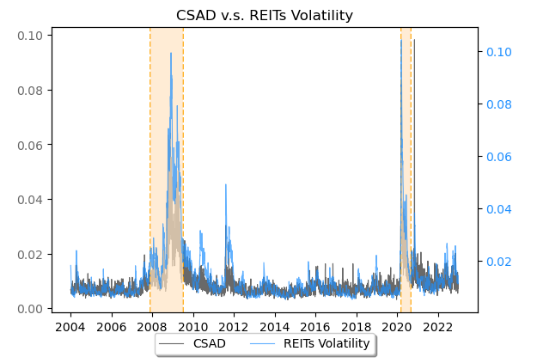
CSAD compare with REITs volatility	Herding proxy compare with REITs volatility
	

Figure 4 Conditional volatility vs. Herding proxy/CSAD for the U.S. REITs market

Note: The dynamic herding proxy is represented by $\gamma_{2,t}$, while $CSAD$ denotes the cross-sectional absolute deviation of REIT returns from the corresponding market portfolio return, represented as R_m. REITs volatility is derived using the GARCH(1,1) model with the REITs market return. This figure visualizes a sample period from January 2004 to December 2022.

In Figure 4, we visually compare the market volatility of REITs with our dynamic herding proxy $(\gamma_{2,t})$ and CSAD, highlighting two turbulent periods: the global financial crisis and the COVID-19 pandemic. This intuitive comparison supports the negative relationship between herding behavior and market volatility. The herding effect is more pronounced during low volatility, and turbulent periods exhibit less herding, helping market prices return to equilibrium (e.g., Holmes et al., 2013; Hwang and Salmon, 2004).

Table 6 Granger causality test result 2

Granger causality				
Pre-listing of the Dow Jones U.S. Select ESG REIT Index: January 5, 2015 to April 25, 2021				
Direction of causality	*Number of lags*	*F-value*	*p-value*	*Decision*
REITs volatiolity →Herding proxy$(-\gamma_{2,t})$	1	5.138	(0.024)**	Yes
Herding proxy$(-\gamma_{2,t})$ *→REITs volatiolity*	1	5.781	(0.016)**	Yes
Green REITs Volatility →Herding proxy$(-\gamma_{2,t})$	1	3.951	(0.047)**	Yes
Herding proxy$(-\gamma_{2,t})$ *→Green REITs Volatility*	1	6.154	(0.013)**	Yes
Post-listing of the Dow Jones U.S. Select ESG REIT Index: April 26, 2021 ~ December, 2022				
Direction of causality	*Number of lags*	*F-value*	*p-value*	*Decision*
REITs volatiolity →Herding proxy$(-\gamma_{2,t})$	1	3.868	(0.050)**	Yes
Herding proxy$(-\gamma_{2,t})$ *→REITs volatiolity*	1	7.287	(0.007)***	Yes
Green REITs Volatility →Herding proxy$(-\gamma_{2,t})$	1	3.432	(0.065)*	Yes
Herding proxy$(-\gamma_{2,t})$ *→Green REITs Volatility*	1	2.973	(0.085)*	Yes

Note: The variable $\gamma_{2,t}$ represents the dynamic herding proxy. REITs volatility is derived using the GARCH(1,1) model with the REITs market return. Green REITs volatility, on the other hand, is derived using the GARCH(1,1) model with the daily return of the Dow Jones U.S. Select ESG REIT Index. It is important to note that the Dow Jones U.S. Select ESG REIT Index was launched on April 26, 2021. Therefore, all data prior to this date is back-tested hypothetical data. To account for this, analysis covers a sample period from January 5, 2015 to December 2022, with a division into two periods: pre-listing (January 5, 2015 to April 25, 2021) and post-listing (April 26, 2021 ~ December, 2022) of the Dow Jones U.S. Select ESG REIT Index. The numbers in parentheses indicate the p-value. * Represent significance at the 10% level. ** Represent significance at the 5% level. *** Represent significance at the 1% level.

In our analysis, we investigate how REITs investors respond to uncertainties in green investing amid the growing interest in environmentally friendly portfolios. To understand their reactions within the broader market context, we adopt a VAR model, expanding it to Equation (3.13) following Dragomirescu-Gaina et al. (2021). This approach enables us to consider both general and asset-specific information sources.

We utilize the Dow Jones U.S. Select ESG REIT Index, a recognized and comprehensive ESG REITs index in the market, to measure green REITs and assess their volatility. Notably, the index was launched on April 26, 2021, and data before this date is considered back-tested hypothetical data. To address this, we divide the data into pre-listing (January 5, 2015, to April 25, 2021) and post-listing (April 26, 2021, to December 2022) periods, allowing us to analyze the impact of the introduction of green investment products in the REITs market on market herding behavior.

Table 6 presents the results of the Granger causality test, showing a dual Granger causality between the herding proxy and two asset-specific information sources: overall REITs market volatility and green REITs volatility. This relationship remains consistent before and after the listing of the Dow Jones U.S. Select ESG REIT Index.

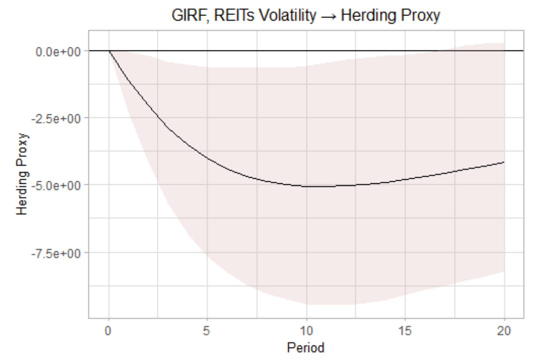
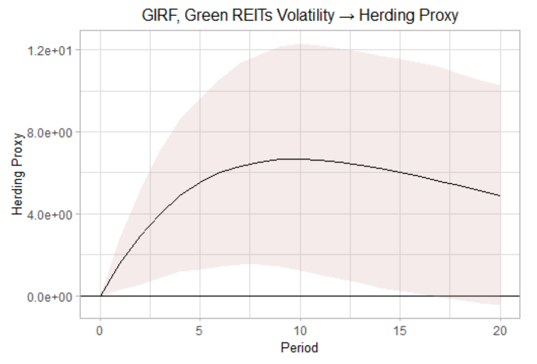
In Figure 5, the GIRFs analysis reveals interesting relationships between herding behavior and asset-specific information proxies. As seen in Figure 3, herding behavior decreases with positive shocks in REITs market volatility. Although the post-listing period has limited data and the results are not statistically significant, we still observe a negative correlation between herding behavior and REITs market volatility, both before and after the listing. This reinforces our previous finding that higher overall market volatility tends to reduced herding behavior.

However, in the case of green REITs volatility, we find that herding behavior increases in response to positive shocks in green REITs volatility before the listing. In other words, prior to the emergence of more representative green commodities in the REITs market, positive shocks in green REITs volatility leads to an increase in herding behavior. This observation aligns with the results presented in Table 4, suggesting that information friction and uncertainty surrounding green investments contribute to higher levels of herding among investors in the REITs market.

Besides, though the data of the post-listing period is limited, we can observe a negative relationship between the herding behavior and green REITs volatility after the listing, which implies that the higher volatility of green assets can stimulate investors to engage in the social learning process and explore the potential of “greener opportunities”. Drawing on the insights of Dragomirescu-Gaina et al. (2021), as investors gain a better understanding of green investments, the investor base that follows market consensus over time becomes smaller, resulting in a decrease in the incidence of herding behavior.

Based on our findings, we propose a conjecture for the REITs market. Initially, investors limited exposure and understanding of green investments, making it challenging to reduce the negative impact of herding. However, as green commodities gain prominence in the market, investors are prompted to engage in a social learning process. The higher volatility of green REITs push investors toward more learning, ultimately leading to a reduction in herding behavior. This aligns with Bikhchandani and Sharma (2000), where better-informed investors disrupt information cascades and mitigate herding effects.

Pre-listing of the Dow Jones U.S. Select ESG REIT Index: January 5, 2015 to April 25, 2021

Herding response to a generalized one SD shock in REITs conditional volatility	Herding response to a generalized one SD shock in green REITs conditional volatility
	

Post-listing of the Dow Jones U.S. Select ESG REIT Index: April 26, 2021 ~ December, 2022

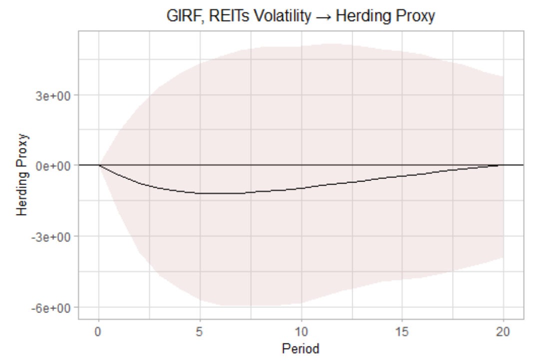
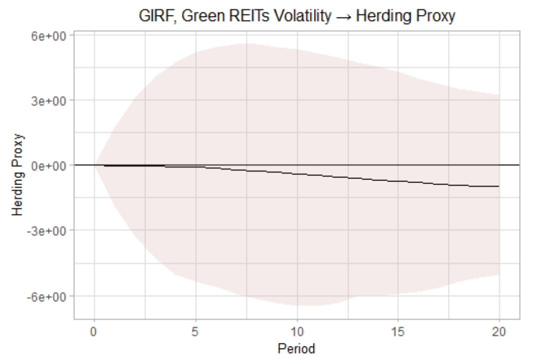
Herding response to a generalized one SD shock in REITs conditional volatility	Herding response to a generalized one SD shock in green REITs conditional volatility
	

Figure 5 Herding responses to REITs asset-specific information shocks

Note: For ease of explanation, in this figure, the dynamic herding proxy is denoted as $-\gamma_{2,t}$, meaning it is multiplied by a negative sign. REITs volatility is derived using the GARCH(1,1) model with the REITs market return. Green REITs volatility, on the other hand, is derived using the GARCH(1,1) model with the daily return of the Dow Jones U.S. Select ESG REIT Index. It is important to note that the Dow Jones U.S. Select ESG REIT Index was launched on April 26, 2021. Therefore, all data prior to this date is back-tested hypothetical data. To account for this, analysis covers a sample period from January 5, 2015 to December 2022, with a division into two periods: pre-listing (January 5, 2015 to April 25, 2021) and post-listing (April 26, 2021 ~ December, 2022) of the Dow Jones U.S. Select ESG REIT Index. The term SD refers to the standard deviation.

Regarding policy implications, early-stage of green REITs investing can lead to herding behavior and mispricing. However, with increased exposure to green commodities, investors engage in social learning, enabling better evaluation of "green opportunities" and informed decisions. Our analyses support Hypothesis *H3*, indicating that the shifting social preference towards green investing in the U.S. REIT market has an impact on investor behavior, leading to increased social learning and influencing herding behavior.

According to Dragomirescu-Gaina et al. (2021), reducing policy-related uncertainty is crucial for portfolios with greener assets. Increased transparency in policy decision-making and better stakeholder engagement before policy changes can mitigate herding and mispricing. Recent efforts by U.S. regulators to promote ESG, such as climate change disclosure by the U.S. Securities and Exchange Commission (SEC) and sustainability reports by NAREIT, encourage REITs to align with climate issues and adopt ESG practices. This enhances sustainability, promotes investors to be better informed about green investments, and contributes to a more sustainable and efficient marketplace.

Chapter 5 Conclusion

This study examines investor herding behavior in the REITs market using a time-varying CSAD herding model. The results reveal that herding behavior changes over time, with the herding effect accumulating during periods of slow market rise and diminishing during certain crisis periods, even showing some instances of anti-herding effects. These findings offer an alternative perspective to previous literature and suggest that crisis periods can act as turning points towards market equilibrium, and also provide additional insight into why previous studies did not observe a pronounced herding effect in the U.S. REITs during the subprime mortgage crisis.

We also investigate the impact of the green investment bandwagon on herding behavior, as well as the relationship between herding behavior and factors such as policy uncertainty and climate change. The findings suggest that as concerns about climate change increase, the herding effect becomes more pronounced, indicating a tendency for investors to blindly follow the market consensus in the early stages of introducing sustainability. However, as the EPU index rises, the herding effect decreases, indicating investor learning and adaptability in the face of policy and regulatory changes.

Furthermore, this study utilizes VAR framework along with tools such as the Granger causality test and impulse response analysis, and reveals a negative association between herding behavior and market volatility. Additionally, we follow the settings of Dragomirescu-Gaina et al. (2021) for the VAR and incorporate the Dow Jones U.S. Select ESG REIT Index as a measure of green REITs. We uncover intriguing results regarding the impact of green volatility shocks on herding behavior before and after listing. The study finds that the herding effect intensifies before the listing but diminishes after the listing in response to green volatility shocks.

We propose a potential conjecture that as green investment develops, herding behavior drives investors towards a social learning process, leading to a deeper understanding of sustainable investment principles and mitigating potential risks. The study emphasizes the policy implications and highlights the importance of ESG practices in promoting the sustainable development of REITs and fostering social learning among investors.

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