



UNIVERSIDADE CATÓLICA PORTUGUESA

# **Herding Behavior in the U.S. REITs market 2013-2023: COVID-19 pandemic outbreak**

Bruno Alexandre Manuel Pinto

Católica Porto Business School

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# Herding Behavior in the U.S. REITs market 2013-2023: COVID-19 pandemic outbreak

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by

Bruno Alexandre Manuel Pinto

Under supervision of  
Phd. Mário Pedro Leite de Almeida Ferreira

Católica Porto Business School  
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## Resumo

O principal objetivo desta dissertação foi avaliar a presença de comportamento de manada no mercado de Fundos de Investimento Imobiliário dos Estados Unidos ao longo da última década. Além disso, tendo em conta o seu início recente, foi fundamental analisar o potencial impacto da pandemia de COVID-19 na intensificação das tendências de manada dentro desse contexto de mercado.

Para alcançar esse objetivo, uma análise foi conduzida por meio da aplicação dos modelos de CSAD desenvolvidos por Chang et al. (2000) e Chiang & Zheng (2010), utilizando um conjunto de dados composto por 130 REITs dos EUA listados na Bolsa de Valores de Nova York, juntamente com o índice de mercado, FTSE Nareit All Equity REITs, abrangendo o período de 2013 a 2023.

Contrariamente às expectativas, os resultados deste estudo não revelaram qualquer evidência de comportamento de herding no mercado de REITs dos EUA ao longo da última década, nem durante o surto de COVID-19, alinhando-se muito mais com as previsões das teorias tradicionais relativas à eficiência do mercado. Estes resultados contribuem para o conhecimento ao mostrar-nos que o mercado de REITs dos EUA pode funcionar de forma mais eficiente do que se pensava anteriormente, aumentando a confiança dos investidores quando se trata de tomar decisões numa base fundamental, em vez de seguir cegamente o rebanho. Além disso, a ausência de uma intensificação do comportamento de manada durante a pandemia da COVID-19 revela um nível de resiliência do mercado imobiliário que, por sua vez, tranquiliza os investidores que procuram estabilidade no meio de crises.

Palavras-chave: Finanças Comportamentais, Comportamento de Manada, REITs, Hipótese do Mercado Eficiente, Mercados de Ações.

# Abstract

The primary purpose of this dissertation was to evaluate the presence of herding behavior in the US Real Estate Investment Trusts (REITs) market over the last decade. Furthermore, considering its recent onset, it was critical to examine the possible impact of the COVID-19 pandemic on increasing herding tendencies in this market scenario.

In order to achieve this goal, an analysis was conducted using Cross-Sectional Absolute Deviation models (CSAD) created by Chang et al. (2000) and Chiang & Zheng (2010) on a dataset of 130 U.S. REITs listed on the New York Stock Exchange (NYSE) and a market index, namely FTSE Nareit All Equity REITs, for the period from 2013 to 2023.

Contrary to expectations, the findings of this study did not reveal any evidence whatsoever of herding behavior in the U.S. REITs market over the past decade, neither during the COVID-19 outbreak, aligning itself a lot more with predictions of traditional theories regarding market efficiency. These results contribute with new findings of the U.S. REITs dynamics by showing that they can operate more efficiently than previously thought, boosting investor confidence when it comes to decision-making on a fundamental basis rather than blindly following the herd. Moreover, the lack of intensified herding during the COVID-19 pandemic shows a level of resilience in the real estate market, which, in turn, reassures investors seeking stability amidst crises.

Keywords: Behavioral Finance, Herding Behavior, REITs, Efficient Market Hypothesis, Stock Markets.

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# Chapter 1

## Introduction

### 1.1 General Background

Mainstream theories such as Efficient Market Hypothesis (EMH), postulate market efficiency and rational decisions of its participants (Fama,1970). However, those theories are challenged as real-world phenomena such as bubbles and anomalies remain difficult to be explained. As a result alternative theories, most noteworthy of those Behavioral Finance, emerged (Shiller,1995). It examines that psychological biases and heuristics condition investor decision-making, indicating market inefficiency to some degree. A key concept in this field is herding behavior, which describes the situation where investors mimic others rather than relying on their own information (Hirshleifer, 2001).

This concept was widely used in the finance literature by important authors to develop main theories that explain some market anomalies such as price bubbles (Avery & Zemsky, 1988), and to explain the intrinsic motivations behind investor intent to herd and its impact in financial markets (Fisher & Statman,2000) such as prospect theory (Kahneman & Tversky, 1979), principal-agent theory (Trueman,1994), and informational cascades (Bikhchandani et al., 1992). Recent research on herding is focused on its impact on emerging markets' efficiency (Ahmad & Wu, 2022); its influence during the pandemic (Maquiera & Méndez, 2022; Bouri et al., 2021); its presence in segments like the cryptocurrency and real estate markets (Youssef & Waked, 2022; Ngene & Gupta, 2023), as well as the role of social media on exacerbating herding in financial markets (Li et al., 2023).

The U.S. real estate market is one of the most valuable globally, with projections to reach \$113.60 trillion in 2023 and an annual growth rate of 4.70%<sup>1</sup> in the next 5 years. A major trend inside this market are the Real Estate Investment Trusts (REITs), which allow investments in real estate properties without directly owning them, thereby providing liquidity advantages. In total, U.S. REITs collectively own more than \$4 trillion in gross assets with 575,000 properties across different sectors (residential, commercial, industrial, healthcare, retail). The major capitalized REITs exhibit moderate concentration, with a total equity market capitalization exceeding \$1.3 trillion for U.S. listed REITs and an average daily dollar trading volume of \$8.0 billion in October 2023<sup>2</sup>. U.S. REITs are subject to interest rate risk, but their diversification, stable dividend-income and potential capital appreciation are attractive for both institutional and individual investors. However, institutional ones have more significant impact on these market movements due to their investment scale and expertise. Thus, evaluating herding behavior in this extremely lucrative and prominent market will be critical for assessing its dynamics, pricing, and stability, particularly during market stress times induced by the COVID-19 pandemic.

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<sup>1</sup> Source: statista.com, April 2023

<sup>2</sup> Source: National Association of Real Estate Investment Trusts (NAREIT), June 2023

## 1.2 Research Gaps

One of the earliest investigations into herding behavior was conducted by Shiller (1995), who studied the dynamics of conversation analysis and information cascades as influencers of herding behavior across groups, leaving room for further exploration of key differences across groups in these dimensions. Alternatively, Avery & Zemsky (1998) focused on the relationship between asset prices and herding, suggesting that herding behavior is less pronounced in cases of higher multidimensionality of prices, but advocated for additional research on this concept. Bikhchandani & Sharma (2000) extended the herding studies to include market conditions, stressing the importance of analyzing emerging markets, as they evidence more herding formation. Adding a new perspective, Kelly & Meschke (2010) emphasized the importance of incorporating the relationship between sentiment and seasonal affective disorders in herding studies.

Recent research has delved into herding behavior during financial crisis, notably during the COVID-19 pandemic. Bouri et al. (2021) studied this phenomenon in the international markets during the pandemic period, highlighting the necessity to analyze if behavioral patterns contributed to volatility jumps. Bogdan et al. (2022) found the research on herding behavior in the context of developed, emerging and frontier European stock markets, particularly appealing amidst the pandemic, offering a window to study this phenomenon in other industry contexts, given their different reactions. Following the previous studies, Maquieira & Méndez (2022) emphasized the need for future research to replicate them using data from a time period that covers the entire pandemic now that the pandemic's end is universally acknowledged.

The herding behavior literature on the REITs market is not extensive, to the best of my knowledge. Niskanen & Falkenbach (2010) emphasized the need to further develop the relationship between REITs, its benchmark assets, and respective impact on herding. Additionally, Akinsomi (2020) highlights the necessity of addressing the role of the information asymmetry in REITs appreciation and its impact on herding behavior. Although some studies of herding behavior on REITS were performed before the COVID-19 pandemic (Babalos et al., 2015; Li et al., 2018; Zhou & Anderson,2013), to the best of my research, studies on herding behavior in the REITs market during the pandemic were only conducted once and in an international context (Lesame et al., 2022).

### 1.3 Research Question

Considering the existing limited literature and presented gaps concerning herding behavior in U.S. REITS especially after the COVID-19 pandemic, this thesis aims to enrich the existing literature and has the primary objective of addressing the following research question: “Is there significant evidence of herding behavior in the U.S. REITs market during the last decade?” and as a secondary goal to analyze the following hypothesis: “Was the COVID-19 an intensifier of herding behavior in the U.S. REITs market?”

This topic is highly relevant because it can provide valuable insights into the financial markets’ response to crisis situations and how investor behavior can impact market dynamics, especially in a sector that previously crashed during the housing bubble in 2007, but conversely has been experiencing projections of enormous exponential growth since the start of the COVID-19 pandemic. Hence, it’s crucial to address whether unprecedented market conditions caused by the pandemic contributed to amplify investor sentiment and reaction towards REITs.

## 1.4 Originality

The originality factors found in my dissertation are as follows: Firstly, the analysis of herding behavior in the pandemic scenario will be conducted in a unique temporal context, given the universal agreement regarding the official end date of the pandemic (May 5<sup>th</sup>,2023), which in turn differentiates itself from the previous studies around the topic (Bouri et al., 2021; Maquiera & Mendez,2022; Elshqirat, 2021; Fei & Zhang, 2023; Madaan & Shrivastava, 2022; Youssef, 2022); Furthermore, it will offer a different perspective of analysis by focusing on a more specific sample, U.S. REITs market, as opposed to the international perspective provided by Lesame et al.(2022); Lastly, to the best of my knowledge, utilizing an updated database, it will be the first study to perform an individual analysis of herding behavior in the U.S. REITs market in a pandemic context.

## 1.5 Contribution to knowledge

The present research aims to contribute to new empirical evidence by analyzing patterns in investor behavior during an unprecedented market crisis, specifically examining whether the pronouncement of herding behavior coincided with specific events or policies during the COVID-19 pandemic and how U.S. REITs reacted during these periods.

Furthermore, there are stakeholders, including investors, policymakers, regulatory agencies like the Security and Exchange Commission (SEC), financial analysts and REITs companies that stand to benefit from this research. Investors may use it to gain insights regarding the herding behavior exhibited by market participants and devise appropriate investment strategies during periods of market turbulence; Policymakers and regulatory agencies would better understand the market dynamics during crises and intervene with suitable

measures to protect the economy and investors from the instability; Financial analysts could incorporate the herding behavior effects into their valuation of REITs companies, enabling more accurate investment recommendations and lastly; REITs companies could use this research to address the impact of herding behavior on their stock prices and develop strategic plans to navigate future crises effectively.

## 1.6 Description of the following chapters

The next chapter, chapter 2, will offer a comprehensive literature review covering market efficiency, behavioral finance, herding behavior and a contextualization of the economy within the U.S. REITs during the COVID-19 pandemic. Following this, chapter 3 will detail the data and methodology used to test the research hypothesis, followed by chapter 4 where the main results will be presented and discussed and, lastly, chapter 5 will summarize the main conclusions drawn from this study.

# Chapter 2

## Literature Review

### 2.1 Concept of Herding Behavior in Finance

Since the recent financial crises, the idea of herding behavior has become more popular in financial literature, with stakeholders attributing market instability and inefficiencies to herding. The propensity of agents to mimic one another's decisions instead of depending on their own information is known as herding (Spyrou, 2013).

According to Shiller (1995), herding occurs as a result of individual interactions, meaning that when people share conversations and ideas, they tend to move into the same direction. According to Bikhchandani & Sharma (2000), herding behavior results from investors' clear desire to follow other people's lead after seeing them make an investment, suggesting a propensity to modify one's initial decision depending on other people's conduct. In response, Hirshleifer & Teoh (2003) recognize that this resemblance in conduct arises from the observation of actions and corresponding outcomes of others. Meanwhile, Hwang & Salmon (2004) suggest that investors disregard private information and rely on others based on market movements such as volume or returns.

The focal point of these concepts lies in the imitation of others, with the distinguishing factor being the motivations behind this behavior. Shiller's (1995) and Hirshleifer & Teoh's (2003) concepts, while valid, may be challenging to identify and somewhat subjective due to difficulties in ascertaining an

individual's inclination before interaction. Hwang & Salmon's (2004) concept, while also valid, lacks incorporation of dimensions that could enhance its point.

Essentially, in the behavioral finance literature, incorporating all the dimensions to develop a complete concept of herding behavior is complex. In this dissertation, the concept of Bikhchandani & Sharma (2000) is adopted as it offers a more comprehensive analysis encompassing essential components of herding behavior, including the intention to imitate, dynamic decision-making, behavioral components and the role of observational influence and interactions in shaping investment decisions in financial markets.

## 2.2. Main theories

### 2.2.1. Efficient Market Hypothesis

Eugene Fama made significant contributions to our knowledge of financial markets dynamics, particularly in the 1960s when he developed the Random Walk Theory. According to this hypothesis, stock price fluctuations are independent and memoryless, which suggests that all available information is already incorporated into current prices and that future price movements will be unforeseeable. Using this concept as a foundation, Fama (1970) presented the initial interpretations of the Efficient Market Hypothesis (EMH), which were later confirmed by Samuelson (1965) and Malkiel (1989). He associated the EMH to the idea of a fair game, meaning that although investors can achieve abnormal returns in the short run, they cannot consistently outperform the market average

over the long run without incurring more risk. Any superior achievement would be credited to luck as opposed to ability.

### 2.2.1.2 Three forms of market efficiency

In order to identify the degree of knowledge that contradicts the market efficiency hypothesis, Fama (1970) proposed three types of market efficiency: (1) weak form, (2) semi-strong form, and (3) strong form.

The weak form contends that because there is little association between historical patterns and future market movements, technical analysis cannot produce extraordinary returns because current stock prices already represent all historical volume and price data. This concept is expanded upon in the semi-strong form, which claims that since stock prices represent all information that is available to the public, it is unlikely that fundamental analysis can provide abnormal returns. According to the strong form, insider information is reflected in both public and private stock prices, making it impossible to beat the market based on any type of information.

### 2.2.1.3 Critics on the Efficient Market Hypothesis

In spite of making substantial contributions towards our understanding of market behavior and providing the foundation for a number of other theories (Sharpe, 1964; Markowitz, 1991; O'Hara, 1999), there are notable challenges that have had to be addressed that have encouraged further research into its limitations. An important challenge in financial markets is the presence of anomalies that contradict the theory that financial markets are efficient. For example, anomalies such as the size effect that was identified by Banz (1981), the

book-to-market, or value effect identified by Basu (1977) and the momentum effect identified by Jegadeesh and Titman (1993). Moreover, the inclusion of noise traders brings an element of irrationality into the marketplace, leading to additional, unattractive risks for rational traders, who may be reluctant to shoulder them, and thus, precipitating substantial divergences between asset prices and their fundamental values prior to subsequent price rebound. This irrationality is further emphasized by Kahneman & Tversky (1974) exalting the presence of cognitive biases in investors' decision-making process. These challenges served as the impetus for the development of the Behavioral Finance field (Kahneman & Tversky,1979; Thaller,1999; Shleifer,2000; Shiller,2000; Ritter,2003). Moreover, the EMH has struggled to explain phenomena such as bubbles and market crises, such as the dot-com bubble in the 90's or the 2008 global financial crisis which demonstrated how investor optimism and enthusiasm led to mispricing of assets, contradicting the notion of rational analysis in the markets (Brunnermeier & Oehmke, 2013). Recently, the speculative nature of the cryptocurrency market has further highlighted the limitations of the EMH (Cheah & Fry,2015).

## 2.2.2 Behavioral Finance

In response to the drawbacks of traditional theories, particularly the EMH, the behavioral finance field emerged in the late 20th century to address these existing gaps by emphasizing the influence of human psychological factors on stock price performance. While the EMH assumes investor rationality, Behavioral Finance suggests that markets are inefficient to some extent. (Hirshleifer, 2015).

Human decision-making processes range from simple to complex, so it's quite impossible to approach each decision rationally. This underscores the

distinction between the rational and intuitive mind: Intuition operates unconsciously, passively, and reflexively, while rationality is active and reflective (Trivers, 2011). Behavioral finance attempts to explain how people make financial choices, and why these decisions may not always appear rational, leading to unpredictable consequences.

According to Shleifer (2000), the Behavioral Finance theory analyzes price dynamics when various types of investors interact and trade in a competitive financial market, wherein some arbitrageurs are assumed to be fully rational. It departs from the traditional idea that markets are solely populated by rational agents and introduces the notion of rationality alongside biases to illustrate market inefficiencies.

### 2.2.2.1 Dimensions of the Behavioral Finance theory

According to Ritter (2003), behavioral finance has two building blocks: (1) cognitive biases and (2) limits to arbitrage.

Cognitive biases represent inherent human systematic pattern deviations from rationality in the decision-making process that often appear in situations of uncertainty. Biases often work as rules of thumb that help the brain simplify received information (Tversky & Kahneman, 1974). According to Hirshleifer (2001) there are four categories that set the biases framework: (1) Heuristic simplification, (2) Self-deception, (3) Emotional loss of control and (4) Social interactions (see table 1).

<b>Categories</b>	<b>Biases</b>	<b>Concept</b>
<b>Heuristic Simplification</b>	Representativeness Heuristic	Tendency to recognize a pattern with uncertain veracity in the presence of limited evidence (Tversky & Kahneman, 1974)
	Framing Effect	Individual interpretation and decision-making based on how the information is communicated (Ritter, 2003).
	Loss Aversion	The feeling of losses overcomes the pleasure of equivalent gains (Kahneman & Tversky, 1984).
<b>Self-Deception</b>	Overconfidence bias	Tendency to overestimate knowledge of the financial markets (Tversky & Kahneman, 1974)
	Hindsight bias	Tendency to believe in the prediction of some events after they occurred (Barberis & Thaler, 2003)
	Conservatism bias	Tendency to sideline beliefs and decisions in the presence of new evidence (Barberis et al., 1998)
	Cognitive Dissonance	Psychological tension created when individual beliefs are at odds (Festinger, 1957)
<b>Emotional loss of control</b>	Ambiguity Aversion	People often prefer to face known risks instead of situations where the probability of distribution of potential outcomes is unclear (Hirshleifer, 2001)
	Mood and Emotions	Tendency to rely on actual feelings and emotions to make a decision (Hirshleifer, 2001).

<b>Social interactions</b>	Contagion Effect	A phenomenon where individual decisions are influenced by a chain in the market (Dornbusch et al., 2000).
	Informational Cascades	Tendency to ignore own information and follow other investors (Banerjee, 1992).
	Herding	The tendency to copy other market participants based on multiple intrinsic motivations (Shiller, 2000).

**Table 1:** Taxonomy of cognitive Biases. Self-elaboration.

Table 1 displays the taxonomy of some of the most common biases and heuristics. Heuristic Simplification occurs when people, in the presence of complex decisions, naturally create mental shortcuts to facilitate decision-making. Self-Deception manifests when people overestimate the power of their capabilities and knowledge about a certain situation only to maintain a positive self-image. Emotional loss of control involves the lack of capability to make rational decisions, as result of an intense emotional state, motivated by the likes of fear or greed. Social interactions, typically refer to the way people will behave after sharing conversations with others, increasing tendencies to herd.

These biases, such as overconfidence or loss aversion, emphasize widespread human behavioral tendencies that, despite not being entirely rational, help us with the understanding of psychological patterns' influence on people's decision-making. As a result, they contribute to the dissemination of similar beliefs, magnifying market movements and therefore producing price deviations from fundamental values, which is a major cause of market inefficiencies (Kuran and Sunstein, 1999).

The second dimension of Behavioral Finance, limits to arbitrage, explores the existence of factors such as transaction costs that prevent arbitrageurs from correcting market inefficiencies. In that sense, arbitrage is crucial for analyzing stock markets as it helps the alignment of prices with their fundamental values, ensuring market efficiency (Shleifer & Vishny, 1997). Although misvaluations of assets are common, profiting from them is not relatively easy. Ritter (2003) identified two types: (1) Recurrent or Arbitrageable and (2) Nonrepeating and long-term in nature. The first type acknowledges situations where it's possible to identify patterns and, with trading strategies, achieve abnormal returns. Instead, the second one, illustrates assets in which it's impossible to identify these patterns in real time, making abnormal returns unachievable.

#### 2.2.2.2 Contributions and Limitations of the Behavioral Finance Theory

The Behavioral Finance theory has considerably contributed to the literature on market behavior by highlighting the role of emotions and cognitive biases, which are frequently disregarded by standard theories used to explain irrational conduct (Ritter, 2003). It recognizes the involvement of psychological elements such as herding or overreaction (DeBondt & Thaler, 1985) as potential contributors to market anomalies and bubbles, such as the dot-com boom of the 1990s, hence studying market dynamics across a range of behaviors (Friedman, 1984; Dreman, 1979).

However, this theory is not exempt of limitations. They are primarily related to the complex nature of the human psyche, which comprises the fundamental core of its research (Shleifer,2000). The complexity of the human mind and its respective cognitive biases and heuristics produce a lack of an argument, limiting the theory's explanatory power. Furthermore, empirical

evidence of Blanchard & Watson (1982) acknowledged that bubbles may not be completely exogenous to rational behavior, calling into question the theory's capacity to properly explain this market phenomenon.

### 2.2.3 Herding Behavior

For animal documentary enthusiasts, it is common to see scenes where preys are running away together from their predators to avoid being caught singled out or even scenes where the female choice of partner is influenced by imitation of others to increase accuracy (Gibson & Hoglund, 1992). While seemingly unrelated to this thesis' context, in fact, these animalistic behaviors offer foundational insights into the fundamentals of herding behavior. Chen (2008) argued for similarities in human behavior, citing examples of ratings' impact in online book purchases.

Keynes (1936) indirectly contributed to early discussions on herding behavior by acknowledging the concept of "animal spirits" to describe how psychological and emotional factors impact investors' decisions during periods of market turbulence. Under this line of thinking, many academics have turned their attention to further exploring these market dynamics.

The herding behavior framework does not provide a single answer for investors' intrinsic motivations to follow crowd tendencies due to the complexities of the human mind, therefore, several academics turned their attention to the development of theories such as informational cascades, payoff externalities, and reputational concerns that can possibly serve as explanation.

### 2.2.3.1 Rational and Irrational Herding

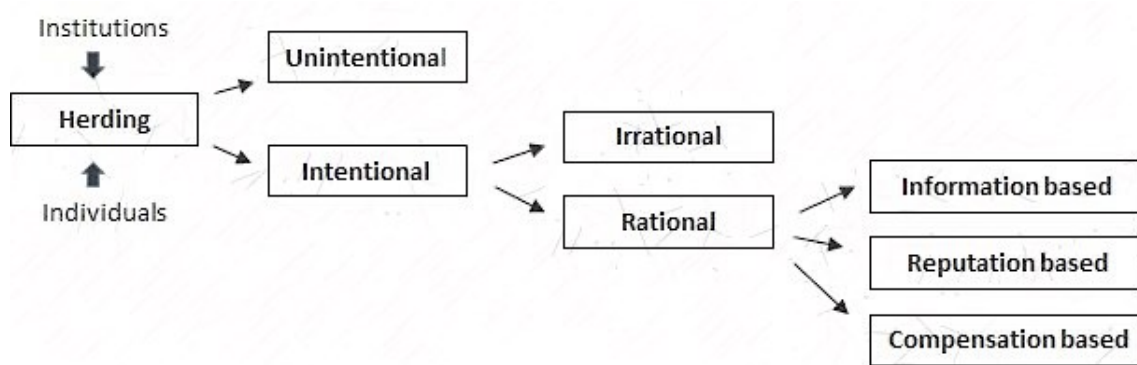
The Behavioral finance theory acknowledges two perspectives of herding behavior: rational and irrational herding (Shiller, 2000).

We are in the presence of irrational herding when investors blindly follow the crowd, disregarding their own abilities and beliefs usually due to lack of sufficient information or improper risk evaluation, leading to impulsive actions. (Lin et al., 2013; Pletcher, 2011). Rational herding, conversely, occurs when individuals make decisions with the crowd because they believe others have superior insights into the same information (Devenow & Welch, 1996).

The literature suggests that these two perspectives often coexist in financial markets depending on investors' approach or market context, therefore it's difficult to distinguish them. However, the decision to follow the crowd while disregarding their own information seems to be a reasonable approach, that's why rational herding tends to be more extensively studied.

### 2.2.3.2 Spurious and Intentional Herding

Bikhchandani & Sharma (2000) proposed a distinction between spurious (unintentional) and intentional herding (see figure 1).



**Figure 1:** Herding Behavior Taxonomy. Source: Bikhchandani & Sharma (2000).

Spurious Herding occurs when individuals mimic others due to shared circumstances, often without full awareness of the outcomes. This behavior stems from relative homogeneity among investment professionals, who share similar educational backgrounds, professional experience, regulatory framework, investing styles and, therefore, the same interpretation of market signals (De Bondt & Teh, 1997; Voronkova & Bohl, 2005; Falkenstein,1996).

In contrast, intentional herding occurs when individuals deliberately follow others' actions to benefit from similar outcomes. The informational payoffs, payoffs externalities, the reputational concerns and compensation schemes are behind the possible causes of this behavior (Bikhchandani & Sharma,2000).

The informational payoffs arise when individuals lack private information due to its high costs or doubt its quality, perceiving others as better informed and

engage in rational utility-maximizing behavior (Devenow & Welch, 1996). This exchange of information can lead to an informational cascade, consequently triggering inefficiencies in the markets (Banerjee, 1992; Bickchandani et al., 1992).

The reputational concerns, related with the principal-agent theory, (Scharfstein & Stein, 1990; Rajan, 1994) motivate herding because a manager's performance is evaluated, and managers may prefer to rely on the benchmark opinions to be safeguarded from negative outcomes instead of risking the opportunity to ascend in the hierarchy. In the end, "bad manager follows good manager", "bad manager looks good" (Trueman, 1994; Zwiebel, 1995).

Managers may also herd if their compensation depends on performance. These managers prefer to abandon the original portfolio after observing the benchmark in order to achieve the same benefits. (Maug & Naik, 1996).

Given the complexity of addressing these motivations separately and pinpointing one as the main cause of herding behavior, Graham (1999) introduced the concept of empirical herding, which clusters all the motivations in order to assess the phenomenon's presence in financial markets.

### 2.2.3.3 Limitations of the Herding Behavior framework

The theories behind the herding behavior explanation entail some limitations. For instance, informational cascades are not straightforward to interpretation given the complexity in discerning whether investors genuinely follow the crowd or simply react similarly to the same new information received in the markets, potentially making rational choices. Payoff externalities' explanation overlook important factors like macroeconomic and regulatory

changes, which can significantly impact them. Reputational concerns are difficult to be qualified as a cause of herding under different market conditions because manager behavior changes during rising markets. These theories did enhance knowledge about the relationship between investor behavior and market dynamics but addressing them separately is quite challenging due to the nature of the human mind and the constant different market conditions, hindering the herding behavior framework.

## 2.3 Empirical evidence on Herding Behavior

Authors	Countries	Period	Context	Herding?
Lakonishok et al. (1992)	U.S.	1985-1989	Institutional herding	No
Grinblatt et al. (1995)	U.S.	1975-1984	Institutional herding	Yes
Nofsinger & Sias (1999)	U.S.	1977-1996	Institutional and Individual	Yes, but higher on individuals
Venezia et al. (2009)	Israel	1994-19997	Institutional and Individual	Yes, but higher on individuals

Table 2: Individual vs Institutional investors.

Table 2 presents the early evidence of herding behavior in financial markets, distinguishing individual and institutional investors because of their different effect on market efficiency. Individual investors tend to follow market trends because they lack expertise and access to information, and as a result they increase market volatility (Barber et al., 2009; Dorn & Sengmueller, 2009; Feng &

Seasholes, 2008). Contrarily, institutional investors are better informed and therefore have more power to either stabilize or destabilize stock prices (Wermers, 1999; Wermers, 1997; Genotte & Leland, 1990; Jacklin et al., 1992). Despite controversies, empirical studies suggest stronger evidence of herding with individual investors. Institutional investors are less susceptible to follow market trends because they have superior access to information, while individual investors, being less informed, are more prone to blindly follow the crowd, emphasizing the degree of information asymmetry as a pattern explaining herding behavior (Nofsinger & Sias, 1999; Choi & Skiba, 2015; Xin et al., 2018; Jiang & Verardo, 2018).

<b>Authors</b>	<b>Countries</b>	<b>Period</b>	<b>Context</b>	<b>Herding?</b>
Christie & Huang (1995)	U.S.	1925-1988	Market-wide	No
Chang et al. (2000)	U.S., Hong Kong, South Korea, Taiwan	1963-1997	Market-wide	No: Hong Kong & U.S. Yes: others
Lee et al. (2013)	China	2001-2011	Market-wide	Yes
Lindhe (2012)	Denmark, Finland, Norway, Sweden	2001-2012	Market-wide	Yes: Finland No: others
Demirer et al. (2010)	Taiwan	1976-1975	Market-wide	Yes
Hassan & Jamil (2021)	Pakistan	2007-2020	Market-wide	Yes

Kumar & Badhani	35 from America, Europe, Asia, Africa, Middle East	2000-2018	Market-wide	Yes: majority from Asia, Africa, and Middle East
Economou (2020)	Croatia, Bulgaria, Romania, Slovenia	2000-2016	Market-wide	Yes
Blasco & Ferreruella (2008)	UK, U.S., Mexico, Japan, Spain, France	1998-2004	Market-wide	Yes: Spain No: others

Table 3: General Herding.

Later on, as presented in table 3, another herding pattern appears to be related to market conditions. Some suggest herding is more intense during bullish markets due to the fear of missing out on high-performing assets (Lee et al., 2013). However, most studies focus on bearish markets, where investors, driven by loss aversion, rush to sell assets in response to economic downturns or negative news (Demirer et al., 2010; Lindhe, 2012; Hassan & Jamil, 2021; Xin et al., 2018; Kumar & Bahdani, 2018; Yasir & Önder, 2023).

Moreover, studies suggest a more pronounced presence of herding in emerging and frontier markets compared to developed markets, with the information asymmetry often cited as a contributing factor (Bogdan et al., 2022; Indārs et al., 2019; Méndez & Arias, 2021; Vo & Pahn, 2019; Economou, 2020). Empirical evidence also points to a more intensified presence of herding in emerging and frontier markets compared to developed markets, with the degree of information asymmetry discussed as a possible explanation (Bogdan et al., 2022; Indārs et al., 2019; Méndez & Arias, 2021; Vo & Pahn, 2019; Economou, 2020). Different herding studies in many developed markets agree with its

presence, although the U.S. usually stands as an exception (Gleason et al., 2004; Chang et al., 2000; Christie & Huang, 1995; Blasco & Ferreruela, 2008; Kumar & Bahdani, 2018). The studies of Chiang & Zheng (2010) and Galariotis et al. (2015) actually found evidence of herding, but only under severe downward market movements, which can suggest a pattern in this market.

<b>Authors</b>	<b>Countries</b>	<b>Period</b>	<b>Context</b>	<b>Herding?</b>
Babalos et al. (2015)	U.S.	2004-2013	REITs market	Yes
Ro & Galimore (2014)	U.S.	1998-2008	REITs market	No
Zhou & Anderson (2013)	U.S.	1980-2010	REITs market	Yes
Akinsomi et al. (2020)	Turkey	2007-2016	REITs market	Yes
Lesame et al. (2022)	27 developed and emerging markets	2019-2021	REITs - COVID-19	Yes – more pronounced during the pandemic

Table 4: Herding Behavior in the REITs markets.

Table 4 highlights the increased academic attention on the real estate sector following the subprime crisis of 2007. Babalos et al. (2015) and Fang et al. (2017) using the regime-switching Markov model were able to detect herding behavior in U.S. REITs during volatile regimes, while opposite results were found when using a static approach. Similarly, Philippas et al. (2013), Zhou & Anderson (2013), Ngene et al. (2017) and Li et al. (2018) detected significant

herding behavior only during turbulent markets. Other studies conducted in different market contexts outside the U.S. also yielded similar results, attributing the uncertainty and information asymmetry as intensifiers (Hott, 2012; Lan, 2014; Akinsomi et al., 2020; Ngene & Gupta, 2023). Opposingly, studies of Yang et al. (2020) and Ro & Gallimore (2014) didn't find herding in U.S. REITs with the latter arguing the assets' transparency as explanation.

<b>Authors</b>	<b>Countries</b>	<b>Period</b>	<b>Context</b>	<b>Herding?</b>
Yasir & Önder (2023)	BRICS	2006-2021	Market-wide – COVID-19	Yes – more pronounced
Bogdan et al. (2022)	15 developed, emerging and frontier countries	2018-2022	Market-wide -COVID-19	Yes – more pronounced
Méndez & Arias (2021)	France, Germany, Italy, UK, Spain	2000-2020	Market-wide- COVID-19	Yes-more pronounced

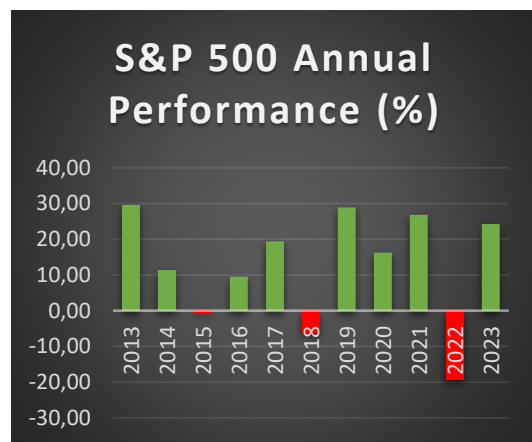
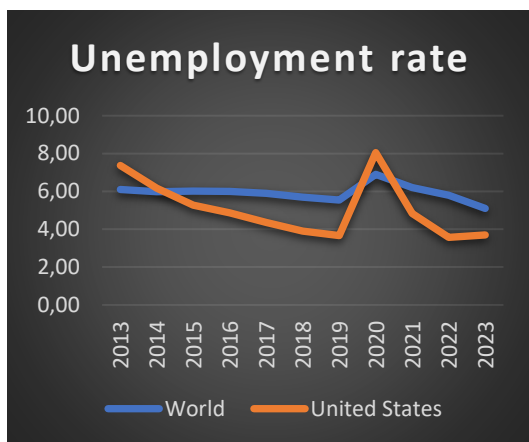
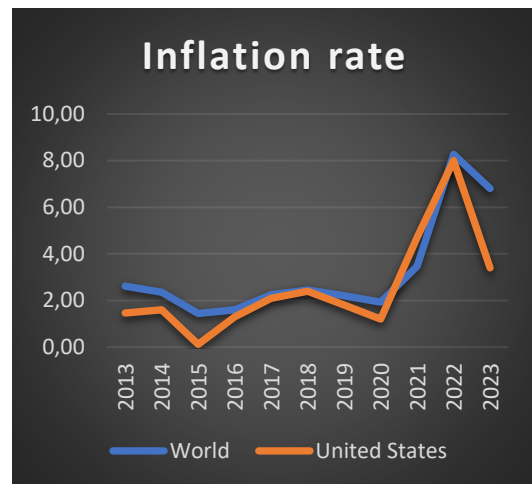
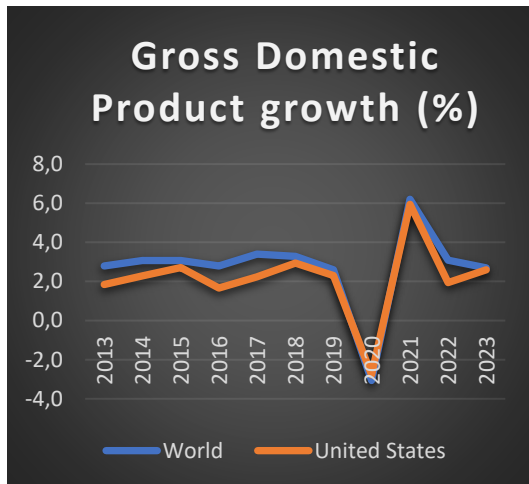
Table 5: Herding Behavior during COVID-19.

Studies also underscore historical events as a possible cause of a significant presence of herding behavior, particularly during unprecedented market conditions and scenarios. A notable example was the internet bubble of 1998-2001 (Singh, 2013). Recently, studies regarding the presence of herding were performed under the COVID-19 circumstances, as displayed in table 5. Ampofo et al. (2023); Nguyen et al. (2023); Dahll & Singh (2020); Lesame et al. (2022) found evidence of herding during the COVID-19 pandemic in both bull and bear markets. Interestingly, studies of Bogdan et al. (2022), Chang et al. (2020),

Alexakis et al. (2023), Bouri et al. (2021) documented less presence of herding in the context of developed markets. These findings suggest that in general the emerging and frontier markets are more subject to herding due to higher level of information asymmetry, whilst in developed markets, like the U.S., significant herding presence is mainly attributed to periods of financial instability and economic downturns.

## 2.4 Context

### 2.4.1 Macroeconomic context from 2013 to 2023



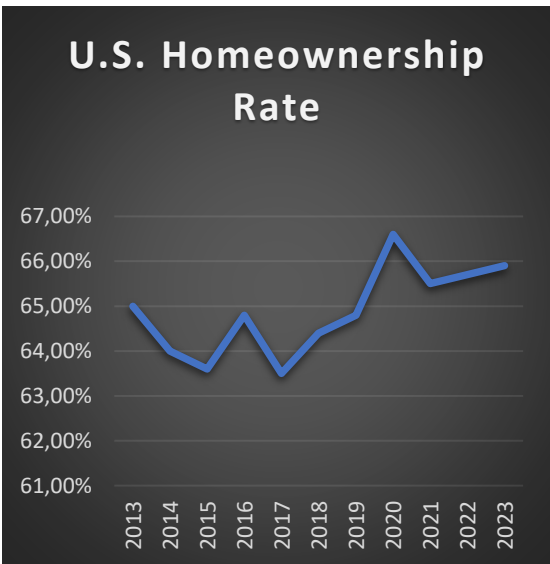
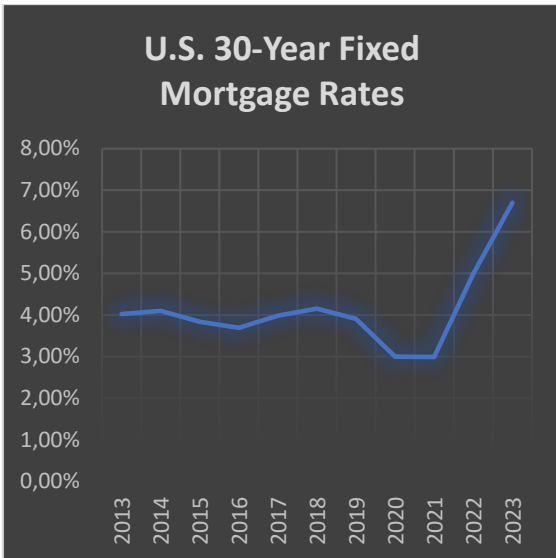
Graphs 1-4: Key Macroeconomic Indicators. Data Source: World Bank

In the last decade, the global economy has endured many momentous occurrences: the Eurozone crisis, regional tensions, regulations, monetary policy reforms, trade conflicts, wars, and a deadly pandemic. Beginning with the slow revival from the 2008 financial meltdown, the U.S. economy accomplished gains in modest increments, due stable monetary policies, improving labor markets, and a healing housing sector. Nonetheless, there were many unknowns such as Brexit, falling commodity prices, and cautious monetary policies, that led to a

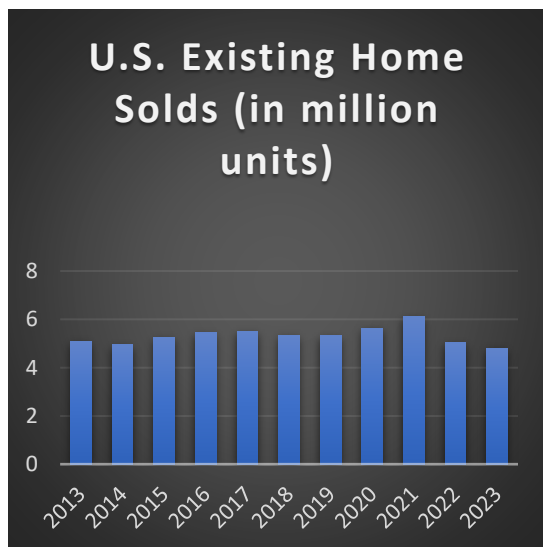
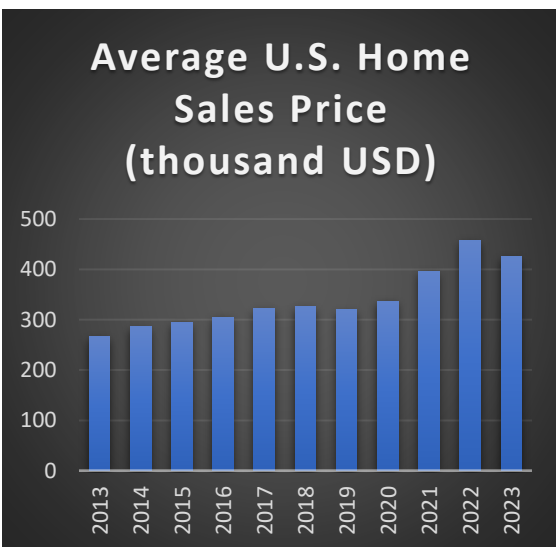
decline in critical macroeconomic indicators in 2016, as shown in graphs 1-4. But with U.S. fiscal policy on overdrive, European economic fundamentals strengthening, and strong demand in emerging economies, we got a global resurgence that resulted in an extended period of bull markets with records highs in stocks in 2019. In 2020, COVID-19 caused a worldwide economic downturn resulting in significant stock market declines and similarly significant turmoil. Within just 12 months, vaccine rollouts started and tranquilized the COVID-19 recession, prompting stock markets to reach new highs, but the subsequent Russian invasion of Ukraine slowed global growth. In 2023, despite ongoing challenges, positive signs emerged, with the WHO declaring an end to the pandemic on May 5th, leading to optimism and positive market reactions as supply chains began to normalize.

## 2.4.2 Sector Overview

Currently, the U.S. real estate market is worth more than \$30 trillion and it is a broad field composed of residential, industrial, and commercial real estate. It operates under characteristics of imperfect competition due to location and product differentiation. A distinct feature is its illiquidity, with the bureaucratic way of doing things in the industry as the main reason. Although illiquid, it lessens the volatility of the market. We have two kinds of investors: individuals, who search for supplemental passive income and institutions for rental and capital gains. Regulatory oversight comes from SEC and the Consumer Financial Protection Bureau ensuring fair housing and anti-discrimination laws.



**Graph 5-6:** U.S. Real Estate Sector indicators. Source: U.S. Census Bureau.



**Graphs 7-8:** U.S. Real Estate Sector indicators. Source: U.S. Department of Housing and Urban Development.

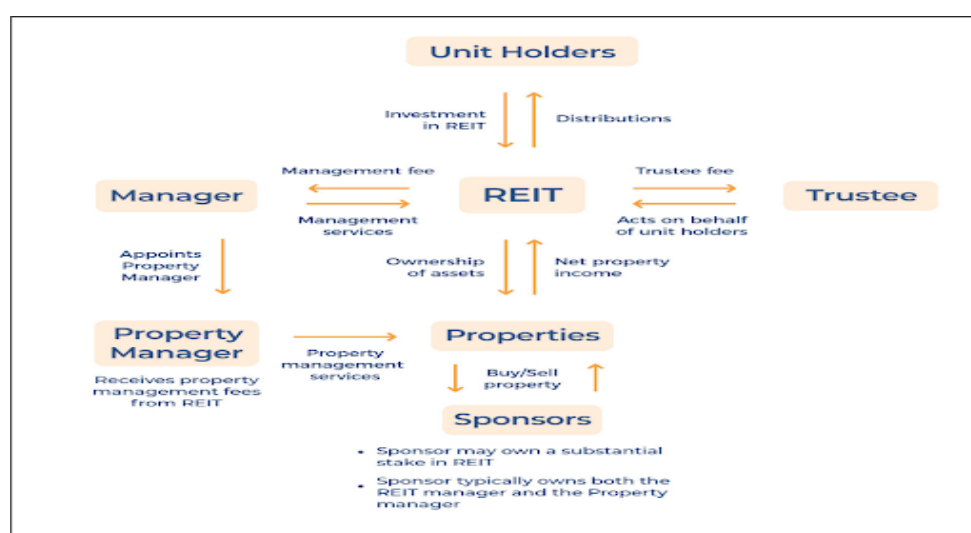
Following the subprime crisis of 2007, the U.S. real estate sector saw a decade-long recovery, fueled by historically low mortgage rates below 4% (see graph 5), programs of quantitative easing and consequent overall market conditions. Challenges imposed by tightening credit conditions, limited inventory and tax reforms adjustments emerged during the decade leading to some unstable periods, as displayed in the graphs 6,7 and 8, but investors reacted with confidence due to the monetary policy enacted. The COVID-19 outbreak in 2020 disrupted the market, but once again, the FED's intervention helped its resilience. However, interest rate hikes and unprecedented levels of mortgage rates impacted buyer activity, raising recession concerns later.

### 2.4.3 Origins and evolution of REITs

In 1960, U.S. REITs were developed by Congress in an effort to provide to all types of investors, particularly smaller ones, access into income-producing real estate. Originally concentrating on ownership and financing, REITs broadened their coverage after the Tax Reform Act of 1986 to include operations and property management.

REITs are companies that own, finance, and operate real estate holdings that generate income in various property sectors (Mazurczak, 2011). Equity REITs are the primary focus of this research since they make up the largest part of the sector, but there are also mortgage REITs, public non-listed REITs, and private REITs. Their structure provides liquid investment opportunities, delivering competitive returns based on stable dividend-income and long-term capital appreciation (see Figure 2). REITs also provide an excellent opportunity for both individual and institutional to diversify their portfolios given their low correlation with other assets.

The interplay of supply and demand greatly influences the REITs market's pricing patterns. Factors such as economic stability, interest rates, the property's intrinsic value, and investor trust all play a significant role in the determination of share price and net asset value. As of October 2023, the listed REITs report a collective total of \$4 trillion in gross assets and an amassed \$1.3 trillion in market capitalization, and an average daily trading volume of \$8.0 billions, with major players exhibiting moderate levels of concentration.



**Figure 2:** REITs Framework. Source: Mendonsa (2021).

The above figure 2 illustrates the REITs framework. For a more detailed explanation of the overall process, please refer to Appendix 1.

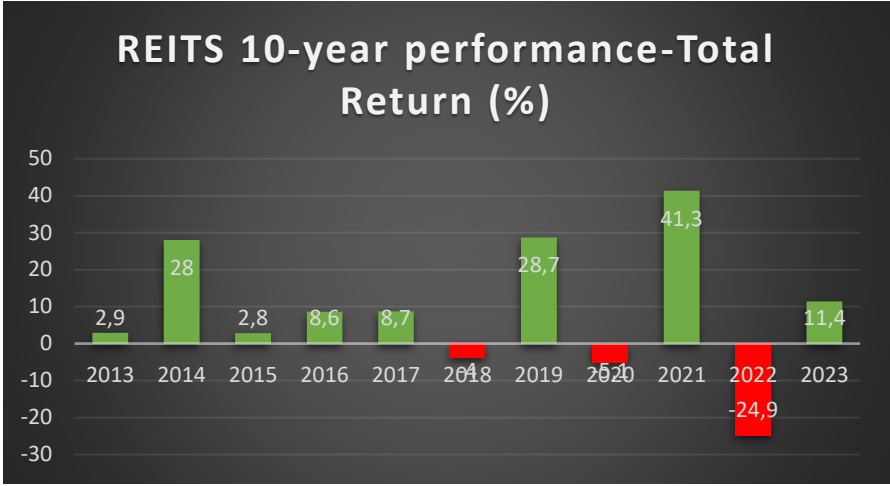
The SEC is responsible for enforcing and overseeing security laws in this market too. Under its regulations, REITs are subject to register with them and make regular disclosures (quarterly financial reports and yearly audited financial reports). Additionally, the SEC enforces a list of requirements to be qualified as a REIT, that are described in Appendix 2.

The FTSE Nareit All Equity REITs index contains 140 publicly listed all tax-qualified REITs with a total net market cap (USDm) of 1,289,117, a dividend yield of 3,92% and entails 20% volatility in the last five years. As of December 2023, the top 5 major players are: Prologis, American Tower Corp, Equinix Inc, Crowne Castle Inc and Welltower Inc with net market capitalizations (USDm) of 122,820, 100,370, 75,079, 49,759 and 48,329 respectively<sup>1</sup>. These five big companies encompass 30,75% of the market share, suggesting moderated levels of concentration.

Over the past decade, notable for technological advances, interest rate fluctuations, economic fluctuations, government policy changes, and a global pandemic, the performance of REITs was significantly impacted by the interest rate dynamics and overall economic conditions. The sector saw significant growth in 2014 following a post-recession recovery, fueled by strong overall economic conditions and lower mortgage rates. However, the performance in the years that followed fell short due to issues such as concerns about trade wars and the interest rates hiking back up. In 2020, the onset of the COVID-19 pandemic disturbed the entire productivity structure, resulting in major volatility and negative returns on the market. In 2021, the sector was reassured, due to fiscal stimulus measures and an effective vaccine roll-out but went into a sharp downturn following the inflation surge and interest-rate hike in 2022. With the display of economic recovery in 2023, a robust performance indeed took place, indicating hope for the future of REITs. Over the decade, though there were some fluctuations, U.S. REITs in general were capable of giving attractive performances (see figure 9).

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<sup>1</sup> Source: FTSE Russell as of 29 December 2023



**Graph 9:** FTSE All Equity REITs performance. Source: FTSE Russel, 29 December 2023

## 2.5 Hypothesis

*H<sub>1</sub>: Herding Behavior is significantly present in the U.S. REITs market during the last decade (2013-2023).*

In the U.S. REITs market, institutional investors' market dominance leads to risks of underperformance relative to industry benchmarks or peers and potential malfeasance relative to compensation. As a result, to enhance reputation and achieve a competitive performance, institutional investors may follow market trends, albeit without fundamental reasons, thereby compromising potential performance and inducing the likelihood of herding behavior.

There are conflicting results in the literature on herding behavior, particularly in developed markets such as the United States. While some experts believe that herding behavior is prevalent and that its intensity varies across different market conditions (Shiller, 1984; Nofsinger & Sias, 1999; Chiang & Zheng, 2010; Demirer et al., 2010; Lee et al., 2013), others who dispute its existence attribute the variation in prices to the different sensitivities of assets to large market returns. Even in the REITs market mixed results have been seen, with most showing that herding behavior is likely (Babalos et al., 2015; Lin et al., 2018; Philippas et al., 2013). In addition, evidence has shown that even throughout the COVID-19 pandemic, this behavior has been evident in the international REITs market, supporting the likelihood of the hypothesis' confirmation (Lesame et al., 2022).

During the last decade, global financial markets saw turbulent times, due to trade controversies, an energy debacle, geopolitical tensions and the COVID-

19 pandemic as well. These events introduced instability to the U.S. REIT market, impaired investor belief, and maybe intensified ruminant actions too. Also, due to long-term lower interest rates, investors were attracted to this market.

Given these disruptions in the economy and the evidence from empirical literature, it's reasonable to expect herding behavior in a moderately concentrated U.S. REITs sector, particularly during periods of economic contraction and bearish markets as in times of unprecedented events, investors may be inclined to mimic others who are perceived to be achieving better results.

*H<sub>2</sub>: The COVID-19 pandemic intensified the presence of Herding in the U.S. REITs market.*

The COVID-19 pandemic had a significant impact on the liquidity and valuations of the U.S. REITs market. The decisions of investors were most likely influenced by a loss-aversion bias, which led them to follow prevailing market trends rather than to rely on their own judgment. Consequently, this behavior might have been instrumental in the emergence of informational cascades and intensified herd behavior in the market. Even though there are conflicting results, the available evidence suggests that investors are likely to behave collectively when they feel unsecure with bad news (Demirer et al.,2010; Xin et al., 2018). Moreover, herding appears to be more prevalent during periods of market turbulence and instability (Lindhe, 2012; Kumar & Bahdani, 2018; Yasir & Önder, 2023), which was the context of the pandemic.

As previously mentioned, REITs are sensitive to interest rates and overall economic conditions. When the economy starts to slow down, it invariably leads

to a disaster in the REITs market. Given the severe magnitude of COVID-19's economic downturn, it is not surprising that these factors damaged investor confidence, exacerbating uncertainty and information asymmetry in this market. Such conditions often prompt investors to rely on the actions of others in pursuit of better outcomes (Lan, 2014; Akinsomi et al., 2020; Ngene & Gupta, 2023). These circumstances enhance the support of the presented hypothesis because even less turbulent conditions once triggered herding behavior in the U.S. REITs market (Zhou & Anderson, 2013).

# Chapter 3

## Methodology and Data

### 3.1 Method

To address the research question, a quantitative analysis was employed to gain comprehensive insights. While qualitative analysis, involving surveys or questionnaires, could provide valuable understanding of individual characteristics related to herding behavior, it is time-consuming, prone to bias, and limited in scope. Conversely, quantitative research focuses on numerical data to generalize findings and establish relationships between variables. Despite potential challenges, such as misleading results, quantitative analysis offers statistical power, meaningful insights, reduced bias, and empirical evidence for future replication. Given the goal of empirically testing theories in finance literature, quantitative research is deemed more appropriate (Babbie, 2010; Muijs, 2010; Lakshman et al., 2000).

### 3.2 Data

The data collection process will utilize secondary data, consisting of observations from a selected sample of 130 U.S. REITs listed on the New York Stock Exchange during the sample period, along with the FTSE Nareit All Equity REITs index (^FNER) serving as the benchmark for the REITs market. The selection of these 130 U.S. REITs was based on their strong representation in the market, availability of data, index's inclusion, and survivorship during the study period, ensuring consistency and robustness in the empirical analysis. The FTSE index is chosen for its historical data accessibility, market representativeness,

robust performance history, and previous use in similar research contexts (Philippas et al., 2013). During data processing, outliers will be included as they are important to assess herding activity under different market regimes (Chiang & Zheng, 2010). Additionally, missing observations will be removed in order to maintain data robustness and reliability. Lastly, in the absence of closing prices due to dividend payments, adjustments will be made by subtracting the dividend from the closing price of the previous day to avoid data bias.

The sample will rely on daily closing prices (USD), under a panel data framework, for all the respective variables during the period of 31/12/2013 to 31/12/2023 (3652 days) extracted from the Yahoo Finance database which is an accessible, reliable, and accurate provider of the data that suits the context of my research and has been widely used and recognized in the financial industry by all its stakeholders (Urolagin, 2017; Khan et al., 2020; Clayton & Schmidt, 2017).

### 3.3 Variables

For all the chosen variables, the 130 U.S. REITs and the given index selected, the FTSE Nareit All equity REITS, calculations of the daily closing prices were performed in order to achieve the daily returns during the period of 31/12/2013 to 31/12/2023 (3652 days). The daily return will be calculated by using the logarithmic return given by the following formula:

$$R_t = \ln \left( \frac{P_t}{P_{t-1}} \right),$$

where  $R_t$  represent the daily return of the market index or the stock price,  $P_t$  the closing price at time t and  $P_{t-1}$  the time prior to closing price.

The preference for calculating logarithmic returns over simple returns stems from several advantages despite its complexity. While simple returns offer simplicity and an intuitive interpretation, they are sensitive to scales and outliers. In contrast, logarithmic returns exhibit a compound nature and are scale invariant, enabling normalized price differences and facilitating long-term comparisons and trend analyses in the REITs market (Roll, 1983; Hudson & Gregouriou, 2015). This approach is supported by several studies due to accuracy in percentage changes, statistical properties, and robustness to outliers, making it particularly suitable for analyzing price sensitivities and conducting studies on herding behavior in the REITs market (Lan, 2014; Ngene et al., 2017).

## 3.4 Main Methodology

### 3.4.1 Cross Sectional Absolute Deviation (CSAD)

The present study employs the CSAD model developed by Chang et al. (2000), considered one of the most suitable approaches for herding studies as it addresses drawbacks of the previous model (CSSD) related with outlier's sensitiveness, linearity in the relationship between the variables and unclear directional aspects (Economou et al., 2011).

The main assumption of this model is that during extreme market movements, market participants are more likely to herd, leading to an increasing or decreasing non-linear relationship between dispersion and market return (Chang et al., 2000; Chiang & Zheng, 2010). This model is expressed by the following formula:

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

where  $R_{i,t}$  is the return of firm  $i$  at time  $t$ ;  $R_{m,t}$  is the market portfolio at time  $t$  and  $N$  is the sample size.

Chang et al. (2000) argued that the level of dispersion is not enough to reveal evidence of herding, but rather it's the relationship between the  $CSAD_t$  and  $R_{m,t}$ , so, to conduct tests on the herding activity, the following regression was performed:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \epsilon_t$$

where  $CSAD_t$  is the average  $AVD_t$ ;  $\alpha$  is the constant;  $R_{m,t}$  is the market return at time  $t$ ;  $|R_{m,t}|$  is the absolute term of cross-sectional market return at time  $t$ ;  $R_{m,t}^2$  is the non-linear term and  $\epsilon_t$ , the error term.

In order to provide more robustness to this model, Chiang & Zheng (2010) presented a variation with the following formula:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 [R_{m,t}] + \gamma_3 R_{m,t}^2 + \epsilon_t$$

This formula considers the investor asymmetric behavior under different market conditions, with a negative and statistically significant  $\gamma_3$  confirming the consistency of the herding behavior formation.

They also presented another variant of the CSAD model which would help to detect intensity of herding under bullish and bearish markets, including a dummy variable  $D^{m,t}$  assuming the value of 0 if  $R_{m,t} > 0$  during bullish conditions and value of 1 with  $R_{m,t} < 0$  under bearish conditions:

$$CSAD_t = \gamma_0 + \gamma_1 (1 - D) R_{m,t} + \gamma_2 D R_{m,t} + \gamma_3 (1 - D) R_{m,t}^2 + \gamma_4 D R_{m,t}^2 + \epsilon_t$$

Since the COVID-19 pandemic introduced different market conditions in the sample of research, this regression will be essential to determine if herding is indeed more present during a crisis.

These models offer insights into the irrationality and volatility observed in market behavior (Javaira & Hassan, 2015).

Despite its complexity and potential interpretation challenges, this CSAD model offer robustness, less sensitivity to outliers and the ability to capture herding formation under various market conditions, therefore, making it a more suitable framework to my research compared to the CSSD model (Galariotis et al.,2015). Therefore, the empirical examination of the hypothesis will rely on the CSAD model, utilizing its model-based OLS estimation due to its interpretability, efficiency, adaptability to the aggregated market variation over time and widespread use and acceptance in finance literature (Francq & Govaerts, 2014).

### 3.5 Software

Although there are some useful and powerful statistical softwares like SPSS, Stata, R, Evi and others, for this research's data processing, I will rely on Python since it's a very versatile, straightforward, powerful, and a robust data analysis tool that have been very used for quantitative finance research, so it will address my sample data with more flexibility than the aforementioned tools (Vallat, 2018; Hilpisch, 2019).

# Chapter 4

## Results

### 4.1 Descriptive Statistics

The descriptive statistics of the market return and the Cross-Sectional Absolute Deviation of the daily returns of the U.S. REITS market ( $\wedge$ FNER) were segmented to assess the impact of the COVID-19 pandemic and the results are summarized in the following table:

Sample	Variables	Mean	Median	Min.	Max.	Std. Dev.	Kurtosis	Skewness	No. of OBS
Full Sample	$R_m$	0,00024	0,00053	-0,1802	0,09584	0,0128	23,68004	-1,20993	2542
	CSAD	0,01077	0,00886	0,00044	0,12806	0,00769	61,51379	6,05791	2542
Pre-COVID	$R_m$	0,00033	0,00069	-0,0193	0,03045	0,00878	2,52673	-0,64526	1536
	CSAD	0,00787	0,00734	0,00175	0,03649	0,00265	14,62482	2,55981	1536
During COVID	$R_m$	0,00011	0,00016	-0,1802	0,09584	0,01722	17,05996	-1,11032	1006
	CSAD	0,01522	0,01285	0,00044	0,12806	0,01031	37,78493	5,05305	1006

Table 6: Descriptive statistics of daily returns (full sample: 31-12-2013 to 31-12-2023; pre-covid: 31-12-2013 to 17-01-2020; during covid: 20-01-2020 to 31-12-2023).

Analyzing the central tendency, we observe positive mean values for both the CSAD and  $R_m$  variables. However, there is a noticeable decrease from the pre-COVID period to the ongoing COVID period, indicating increased volatility during the pandemic, as supported by higher standard deviation values. Maximum and minimum values provide insights into the magnitude of extreme values throughout the period, with values for the full sample matching those of

the COVID sample, indicating heightened dispersion due to the pandemic. Kurtosis and skewness interpretations remain consistent across all periods, signaling the heavy impact of the pandemic on the sector. A negative skewness of the  $R_m$  variable indicates a longer left tail, suggesting a higher frequency of extreme negative returns, while the positive kurtosis value indicate that the distribution of daily returns is highly leptokurtic and it's highly peaked with fatter tails. Conversely, positive skewness of the CSAD variable suggests a higher frequency of extreme positive values, and its higher kurtosis confirms a leptokurtic distribution with heavy tails and a sharp peak.

## 4.2 Main Results

In order to infer the possibility that herding behavior may have been present in the U.S. REITs market during the last decade, the CSAD model of Chang et al. (2000) was employed together with the variation of Chang & Zheng (2010) to verify the result's robustness. Table 7 displays the results of the regression model:

	<b>Coefficient</b>	<b>Std. Error</b>	<b>t-stat.</b>	<b>P-value</b>	<b>Adj. R-Squared</b>	<b>F-test</b>
$\alpha$	0,0074	0,0002	39,2745	0,0000***	0,31414	582,93***
$\gamma_1$	0,3795	0,0220	18,4063	0,0000***		
$\gamma_2$	0,9151	0,2428	3,7698	0,0002***		

Table 7: Estimates of herding behavior in the U.S. REITs market.

Regression model:  $CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \epsilon_t$

\*\*\* Significant at the 5% level.

The results show that for all estimations, the explanatory power, measured by the adjusted R-Squared suits the model and is consistent with findings from

similar studies (Chiang & Zheng, 2010). Additionally, the F-test prove the significance of the model.

Upon examining the variable's significance, the results indicate that for the sample period, all coefficients on the linear term  $R_{m,t}$  ( $\gamma_2$ ) are positive and statistically significant (0,9151), suggesting that the cross-sectional absolute deviation of returns actually increases with the market and the dispersion of equity returns continues to increase linearly, therefore indicating absence of herding behavior in the U.S. REITs market.

Aiming to validate the presented results, the variation of Chiang & Zheng (2010) was employed, displaying the results in the following table 8:

	<b>Coefficients</b>	<b>Std. Error</b>	<b>t-stat.</b>	<b>P-value</b>	<b>Adj. R-Squared</b>	<b>F-test</b>
$\alpha$	0,0075	0,0002	39,6499	0,0000***	0,3222	403,71***
$\gamma_1$	0,05676	0,01014	5,5978	0,0000***		
$\gamma_2$	0,36830	0,02059	17,8789	0,0000***		
$\gamma_3$	1,2220	0,2475	4,9358	0,0000***		

Table 8: Estimates of herding behavior in the U.S. REITs market.

$$\text{Regression model: } \text{CSAD}_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 [R_{m,t}] + \gamma_3 R_{m,t}^2 + \epsilon_t$$

\*\*\* Significant at the 5% level

The results were able to validate the conclusions previously stated regarding the absence of herding behavior by looking at the positive and significant coefficient of  $\gamma_3$  of 1,2220 during the sample period.

To examine the impact of COVID-19 on the possible presence of herding behavior in the U.S. REITs market, a COVID-19 dummy variable was included in the CSAD model to represent the days that cases were reported in the U.S., taking

values of 1 during COVID-19 periods and 0 otherwise. This CSAD model was expressed in the following way:

$$CSAD_t = \alpha + \gamma_1 D^{covid} |R_{m,t}| + \gamma_2 (1, -, D^{covid}) |R_{m,t}| + \gamma_3 D^{covid} R_{m,t}^2 + \gamma_4 (1, -, D^{covid}) R_{m,t}^2 + \epsilon_t$$

Negative and statistically significant coefficients of  $\gamma_3$  and  $\gamma_4$  would manifest herding behavior in the U.S. REITs market during present and absent COVID-19 periods, respectively.

The results are presented in the following table 9:

	<b>Coefficients</b>	<b>Std. Error</b>	<b>t-stat.</b>	<b>P-value</b>	<b>Adj. R-Squared</b>	<b>F-test</b>
$\alpha$	0,0063	0,0002	34,9068	0,0000***	0,43707	494,22***
$\gamma_1$	0,0562	0,0092	6,0896	0,0000***		
$\gamma_2$	0,2840	0,0191	14,8521	0,0000***		
$\gamma_3$	1,5383	0,2259	6,8091	0,0000***		
$\gamma_4$	0,0058	0,0003	22,8641	0,0000***		

Table 9: Estimates of COVID-19's impact on herding behavior in the U.S. REITs market.

\*\*\* Significant at the 5% level.

The coefficients  $\gamma_3$  and  $\gamma_4$  are positive and statistically significant, confirming firstly the previously stated absence of herding behavior in the U.S. REITs market in this sample and thus contradicting a possible assumption that investor's intent to ignore private information and rely on the market's direction in the U.S. REITs market could have been caused by the COVID-19 pandemic outbreak.

## 4.3 Discussion of results

### 4.3.1 Hypothesis 1

The main hypothesis of this dissertation posited the presence of herding behavior in the U.S. REITs market over the last decade. However, contrary to expectations, applying the CSAD model by Chang et al. (2000) and a variation of Chiang & Zheng (2010), the findings revealed positive and significant coefficients of  $\gamma_2$  and  $\gamma_3$ . Hence, the dispersion of equity returns increased linearly with the market return, rather than non-linear, suggesting an absence of herding behavior. This finding supports the prediction of rational asset pricing models.

Herding behavior typically arises from informational cascades, where individuals rely on others due to a lack of adequate information (Bikhchandani et al., 1992). However, in the U.S., financial markets benefit from low levels of information asymmetry thanks to well established regulatory frameworks and transparent reporting standards, especially in a REITs market regulated by the SEC. This reduced level of information asymmetry may have mitigated the development of informational cascades, lowering the likelihood of herding behavior. Additionally, the traumatic experience of the 2008 global financial crisis may have contributed to a more cautious approach among investors in the U.S. REITs market, prompting them to adopt a more risk-averse stance towards informational cascades and consensus-based actions, emphasizing the equal potential positive impact of biases and heuristics discussed by Tversky and Kahneman (1974).

Despite the limited literature on herding behavior in the REITs market, several studies support the findings of this research regarding its absence in U.S. financial markets (Lakonishok et al., 1992; Christie & Huang, 1995; Chang et al.,

2000; Gleason et al., 2004; Chiang & Zheng, 2010; Blasco & Ferreruela, 2008; Kumar & Bahdani, 2018). Studies within the U.S. REITs market, such as those of Yang et al. (2020) and Ro & Gallimore (2014) concluded that herding behavior didn't affect the returns in this sector, with the latter arguing the transparency of REITs as one of the main reasons. Even studies that documented a herding presence in this sector, covered periods including the 2008 global financial crisis (Zhou & Anderson, 2013; Philippas et al., 2013), suggesting that different periods and statistical techniques may yield mixed results.

### 4.3.2 Hypothesis 2

The secondary aim of this research was to assess how the COVID-19 pandemic influenced the formation of herding behavior in the U.S. REITs market. Surprisingly, the positive and significant value of the coefficient  $\gamma_3$  in the table 9 confirmed the absence of herding in the U.S. REITs market during the COVID-19 pandemic.

The prospect theory, primarily focused on loss aversion, reveals that investors are prone to misjudged tendencies in their risk-related decisions (Kahneman & Tversky, 1979). The COVID-19 outbreak brought in enormous turmoil in global financial markets, leading investors to a more conservative approach, possibly lessening their inclination to herd. Their ultimate motives, in this case, have prioritized capital preservation or investment in safer assets from the U.S. REITs.

After the global financial crisis of 2008, the U.S. changed the rules for the financial industry. The changes were meant to make the system better. As the

financial system changes, companies' networks become an important way to understand what is happening. Moreover, technological innovations took place, and new technologies mean that the world of finance is more accessible, and the dissemination of information is more flexible.

The available research on the effects of COVID-19 on herding behavior is limited since the pandemic only recently took place. Still, some studies have presented differing results, consistent with my findings, some authors have shown that there was no herding during the pandemic in developed markets (Alexakis et al. 2023; Bogdan et al. 2022; Chang et al. 2020; Bouri et al. 2021). Still, with respect to REITs, to the best of my knowledge, only Lesame et al. (2022) have taken the pandemic's impact on the REITs market in a global context and have disclosed herding activities during this period. It should, however, be stated that this study covers the entire pandemic period, as it uses more recent data following the announcement by the WHO about the pandemic's end, so differences in sample periods may contribute to these different results.

# Chapter 5

## Conclusion

### 5.1 Main conclusions

The primary aim of this thesis was to conduct an empirical examination of herding presence in the U.S. REITs market over the most recent decade. Also, it tried to evaluate any possible change in investor behavior due to the COVID-19 pandemic, which led to turbulent periods. To achieve this objective, the CSAD model (Chang et al., 2000) was utilized with a dataset of 130 publicly listed U.S. REITs and the FTSE NAREIT REIT Index from 2013 to 2023.

The results showed that, contrary to expectations, there was no evidence of herding in the U.S. REITs market, thus supporting the prediction of traditional rational asset pricing models regarding market efficiency. These findings shed light on the efficiency of the U.S. REITs market during this period, suggesting that investors likely made informed and rational decisions, incorporating available information to drive price movements that accurately reflect underlying asset values, aligning with the EMH theory.

Although this study didn't yield the expected results, it emphasizes the complexity of investor behavior and respective market dynamics. This research also offers important academic contributions to the understanding of herding behavior dynamics in the U.S. REITs market given the limited research in this sector, especially regarding the pandemic impact on herding. Furthermore, by exploring different theoretical and empirical perspectives, this research underscores the importance of recognizing how different methodologies can lead

to mixed results, emphasizing the need for ongoing refinement in the methodologies used to capture herding behavior. Lastly, this research enriches the existing literature by addressing the context of REITs' dynamics themselves when detecting herding behavior, shedding light on how investors react to different market conditions and contexts.

## 5.2 Implications for management

The main findings of this research provide insightful information regarding U.S. REITs dynamics that can be very useful to investors, policymakers, regulators, financial analysts and even REIT companies themselves.

For REITs investors, due diligence and independent research are crucial to navigate through changing market conditions and monetary policy dynamics, mitigating risks associated with potential market volatility and mispricing of assets induced by herding behavior. For policymakers, it is advisable to maintain efficient regulatory frameworks to promote transparency and investor protection, while enhancing surveillance mechanisms to detect and prevent market irregularities. For the Security and Exchange Commission, it's important to maintain diligent enforcement efforts to discourage fraudulent behavior in the U.S. REITs market and act quickly to bring offenders accountable by enhancing surveillance mechanisms to monitor irregular trading patterns. Additionally, updating and refining disclosure requirements would be essential to ensure investors have access to timely and accurate information, thereby facilitating informed decision-making. Financial analysts should prioritize a comprehensive fundamental analysis on REITs, assessing the impact of different market conditions on its performance, advocating for greater transparency and

disclosure standards to ensure a reliable analysis. For REIT companies, it's important to maintain transparent communication, compliance with its stakeholders, and prioritize sustainable development initiatives in order to enhance market credibility and stability.

### 5.3 Limitations of research

Despite the prominent contributions of this study, it is essential to acknowledge its inherent limitations, which may restrict the generalizability and robustness of the findings.

Firstly, this study is subject to a sample selection bias since the selection of the U.S. REITs has considered its survivorship and representativeness over the last decade, which can limit the generalizability of the results to the broader REITs market. Furthermore, this study is based on the standard CSAD models endowed with assumptions and simplifications regarding investor behavior, market dynamics and economic conditions. However, despite being necessary for modelling processes, they may not capture the real complexity of the world, which can lead to misinterpretation of results. Lastly, interpreting the results of this study presents significant challenges when considering the inherent complexity of herding behavior nature, leading therefore to potential biases or alternative explanations when interpreting the observed outcomes.

## 5.4 Future Research

Future research could focus on investigating herding behavior in the U.S. REITs market to address existing gaps in our understanding, given the scarcity of literature on this topic.

Additionally, it can also be of great interest to extend the time period of the research incorporating periods from the global financial crisis to the pandemic outbreak, in order to capture the key differences exhibited in investor behavior. It can also be helpful to include other control variables into the analysis, like trading volume or market volatility, to better understand if it can be determinant for herding behavior. Further research should also focus on developing alternative regression models to test the presence of herding behavior given the mixed results exhibited in the literature in order to provide a more robust framework.

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# Appendices

## A1. Figure 2

The figure 2 describes the REIT framework that begins with sponsors, who could be builders or individuals involved in property transactions, deciding to establish a REIT company, and holding a significant stake. These sponsors then appoint trustees responsible for holding legal title to the assets on behalf of unitholders, ensuring legal compliance, and typically remaining independent from the management team. Unitholders, who can be institutional or individual investors, purchase units of the REIT company and are entitled to receive distributions. The REIT manager oversees asset management and investment decisions, receiving fees from the REIT company, often calculated as a percentage of net income or total assets. The choice between active and passive management strategies depends on the REIT's goals and philosophies, although passive strategies are often favored for cost efficiency. Independent directors may form a board to provide unbiased oversight, safeguarding unitholders' interests, with additional committees comprising auditors, registrars, transfer agents, and merchant bankers handling operational activities.

## A2. Requirements for qualification as a REIT

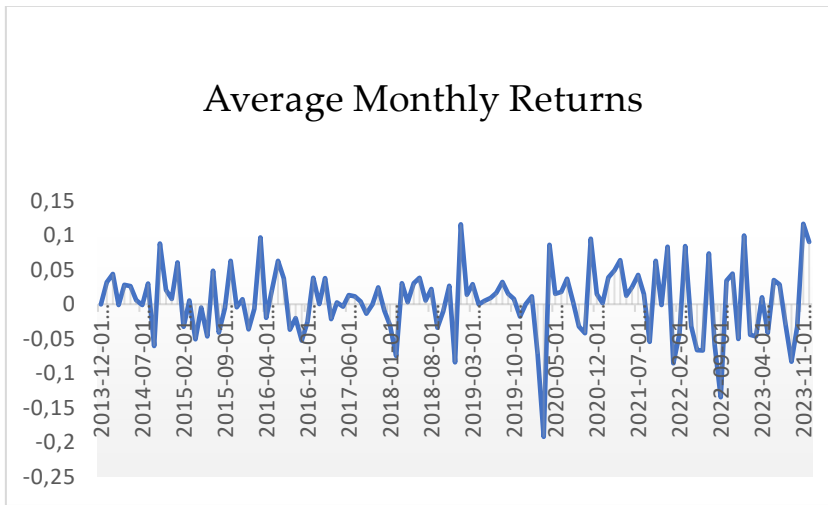
The requirements for qualification as Real Estate Investment Trust, as defined by the Security and Exchange Commission, are as follows:

1. Invest minimum of 75% of its total assets in real estate.
2. Generate a minimum of 75% of its total income from renting out real properties, earning interest on mortgages that finance real properties, or through the sale of real estate.
3. Pay at least 90% each year of its taxable income in shareholder dividends.
4. Be a taxable corporation.
5. Be managed by a board of directors.
6. Have minimum 100 shareholders and have no more than 50% of its shares held by five or fewer individuals.
7. Derive at least 95% of its gross income from such real estate sources and dividends or interest from any source.
8. Have no more than 25% of its assets consisting of non-qualifying securities or stock in taxable REIT subsidiaries.

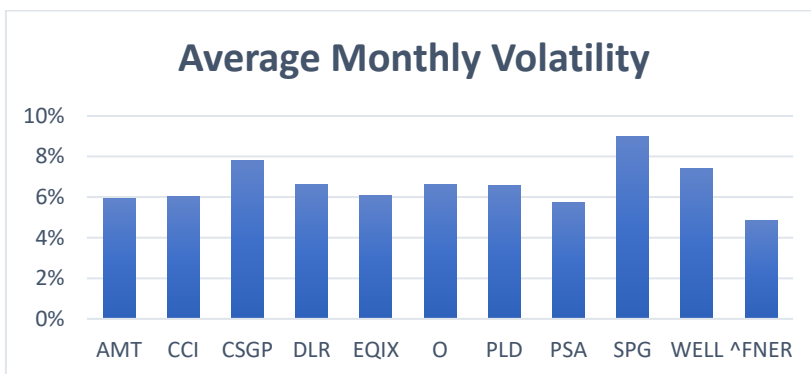
A company that qualifies as a REIT is allowed to deduct from its corporate taxable income all dividends paid out to its shareholders.

(Source: NAREIT, 2023)

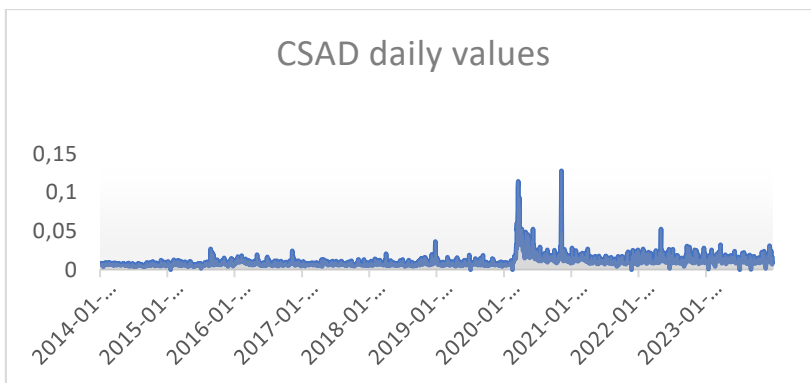
### A3. Graphs



**Graph 10:** Average monthly returns in the U.S. REITs market during the last decade.



**Graph 11:** Average monthly volatility of returns of the top10 major U.S. REITs during the last decade.



**Graph 12:** CSAD daily values.

