Signal herding and contrarianism in REITs - dissemination of stock vs fixed income factors

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Signal herding and contrarianism in REITs – dissemination of stock vs fixed-income factors

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Abstract

Herding and contrarian behaviours in financial markets have drawn significant attention due to their potential to distort prices. In the Real Estate Investment Trusts (REITs) market, both behaviours have been observed, though explanations often remain anecdotal. This paper provides further insights into herding and contrarianism in US equity REITs by analysing their inherent characteristics and the impact of exogenous informational signals. Our findings reveal frequent and prolonged contrarian behaviour, contrasted with sporadic and brief herding episodes at both the market and sub-sector levels. Our results highlight the dual nature of REITs, where return dispersions differ inherently between their stock and fixed-income characteristics. Moreover, information spillovers from the stock and debt markets, as well as signals from larger REITs, drive distinct investor behaviours. We also observe that herding tendencies increase when investors shift capital from the stock market and that excess return dispersion intensifies during recessions, reflecting a heightened reliance on private information in times of crisis.

Keywords Herding · REITs · Contrarianism · Fundamental · Signal

JEL Classification C22 · G23 · G40

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1 Introduction

Herding is widely defined as the behaviour of market participants who mimic the actions of others while disregarding their own private information (Bikhchandani and Sharma 2001; Demirer and Kutan 2006; Spyrou 2013). In contrast, contrarians trade against prevailing market trends or past trades (Avery and Zemsky 1998; Drehmann et al. 2005), a behaviour often referred to as anti-herding or reverse herding in the literature. Understanding these behaviours is crucial from both regulatory and investment perspectives (Philippas et al. 2013), as they can distort prices and intensify market volatility (Park and Sabourian 2011).

This paper focuses on investors' herd and contrarian behaviours in the equity Real Estate Investment Trust (REIT) market. Since their introduction in the 1980s, REITs have grown significantly in both size and importance, offering a more liquid way of investing in real estate. Publicly traded REITs share similarities with stocks but are influenced by real estate factors such as rental income (Boudry et al. 2012; Clayton and MacKinnon 2003; Hoesli and Oikarinen 2012). Unique in structure (e.g. 90% pay-out of their income as dividends) and characteristics (e.g. small cap and low trading volumes) (Zhou and Anderson 2013), REITs are more volatile to exogenous shocks (Anderson et al. 2012) and exhibit a significant level of risks (Zhou and Anderson 2012).

Given REITs' unique characteristics, and their significance in price determination in direct real estate (Barkham and Geltner 1995; Seck 1996), scholars have made a few attempts to examine herding in REITs (Babalos et al. 2015; Essa and Giouvris 2023; Philippas et al. 2013; Zhou and Anderson 2012). While both herding and contrarianism are evident in these studies, the explanations for such behaviours are somewhat anecdotal, and evidence of contrarianism is often overlooked.

Indeed, the challenge of empirically pinpointing the specific sources for herding behaviours has been widely acknowledged (Bikhchandani and Sharma 2001). In finance studies, studies have found that investors herd on market fundamentals in certain markets (Galariotis et al. 2015). By the same token, REITs investor behaviour may be attributed to price changes in underlying fundamentals, such as the stock market and fixed-income sectors.

Theoretically, much discussion on herding is on informational cascades (Banerjee 1992; Bikchandani et al. 1992; Hirshleifer and Hong Teoh 2003; Welch 2000), particularly when the market is uncertain about asset values (Avery and Zemsky 1998). Investors may herd or exhibit contrarianism due to the type of informational signals they receive (Park and Sabourian 2011; Park and Sgroi 2012). Signals from related markets often begin as spillovers but can evolve into collective signals driving irrational behaviour (Philippas et al. 2020). In the REIT market, where liquidity is influenced by private information (Danielsen and Harrison 2000), investors are likely to react to such signals.

Against this background, using daily equity REIT price data from the CRSP Ziman REIT database for the period January 1980 to December 2021,[1] this paper seeks to expand empirical evidence on herding and contrarianism in REITs while exploring the potential sources of these dynamics.

We first adopt the empirical approach in Chang et al. (2000) to examine if return dispersion, measured by the cross-sectional absolute deviation of returns (CSAD), decreases (increases) non-linearly against the overall market return, indicating investor convergence towards (divergence from) the market consensus and thus evidence of herding (contrarian-

[1] Which is free of survivorship bias.

ism). We do so at the whole REITs market level as well as at sub-sector levels. Our results show periods of both herding and contrarianism, with contrarianism being the dominant behaviour in the overall REITs market and most REITs sectors.

Second, we examine whether herd and contrarian behaviours observed in the existing studies are specific to the inherent characteristics of REITs. Empirically, we dissect dispersion in REITs returns into two components: one attributable to fundamental stock market factors, as documented in Galariotis et al. (2015) using Fama-French and other stock market pricing factors; and another attributable to fixed-income asset factors. Our results show that investors predominately trade against the market consensus and engage only infrequently in herding based on both stock and fixed-income information. Moreover, the findings suggest that REIT investors' behaviour is jointly influenced by conditions in equity and fixed-income markets.

The last part of our empirical strategy is motivated by informational signal herding literature (Avery and Zemsky 1998; Park and Sabourian 2011; Park and Sgroi 2012). Allowing a range of information structures, informational signals may prompt investors to either converge with or diverge from the market consensus (Philippas et al. 2020). Empirically, we derive such 'informational signals' from a range of potential exogenous measures encompassing the general stock market, bond markets, and market sentiment, as well as a set of measures within the REITs markets. In addition, we include a flight to safety (FTS) measure (Baele et al. 2020; Boudry et al. 2022). Our results show that these signals intensify or dampen the degree of herding and contrarian behaviour in REITs, underscoring the significant role of informational signals in shaping investor behaviour.

This paper contributes to the REIT literature in several ways. To our knowledge, it is the first study to dissect REITs' inherent characteristics and examine how these influence investment behaviours. Complementing previous studies that focus on aggregated return changes, we derive signals from other markets and macroeconomic sentiments while accounting for REIT return dynamics. We demonstrate that herding and contrarian behaviours tied to stock and fixed-income fundamentals are affected differently by such signals. Additionally, we provide new insights into intra-REIT dynamics, showing that 'representative' REITs play a significant role in shaping distinct investor behaviours. By incorporating rolling window analysis, we offer additional insights into the time-varying nature of herding and contrarianism, capturing dynamics across different economic states.

Publicly traded REITs play a key role in price determination in direct real estate markets (Geltner et al. 2003). Consequently, investor behaviour in REITs can significantly impact the broader real estate sector (Philippas et al. 2013). This paper contributes to discussions on price discovery, investor sentiment, and the interplay between REITs, stock markets, and direct real estate markets. Observed levels of herding and contrarianism also provide insights into the transparency of REIT stocks (Ro and Gallimore 2014). By examining informational signals, this study introduces a new dimension to the debate on REIT market transparency. Additionally, from a portfolio perspective, the findings offer valuable insights for market practitioners, as REITs constitute a significant portion of alternative investment holdings (Zhou and Anderson 2013).

The rest of this paper proceeds as follows. Relevant literature is reviewed and discussed in Section 2. The details of our empirical strategies are explained in Section 3, followed by data description in Section 4. We present and interpret our empirical findings in Section 5. Finally, Section 6 concludes this paper.

2 Literature review

2.1 Herding literature and Herding/contrarianism in REITs

Herding and contrarianism can arise from various drivers. Herding can be a rational response in markets where acquiring private information is costly. Agents may underweight their private signals in the presence of noise, leading to herding behaviours (Vives 1993, 1997). This effect is amplified among short-term speculators, who often rely on limited, potentially low-quality information sources, resulting in informational inefficiencies (Froot et al. 1992). Additionally, market sentiment plays a crucial role in encouraging herding, as shown by studies linking it to behavioral biases and social influences (Devenow and Welch 1996; Hwang and Salmon 2009; Shiller et al. 1984). Institutional factors such as fund managers' reputational concerns and performance-based compensation structures also contribute to herding tendencies (Bikhchandani and Sharma 2001; Graham 1999; Scharfstein and Stein 1990; Trueman 1994).

Contrarians, by contrast, trade independently from herds. Wei et al. (2015) argue that reputation-based herding models predict contrarians to outperform their peers due to independent private information. However, overconfidence in private signals, combined with underweighting public information, may lead to underperformance (Daniel et al. 1998). Engaging in excessive risk may also drive certain investors to deviate from the herd, such contrarians are likely to be prone to agency issues and thus under-perform as well (Wei et al. 2015). In addition to overconfidence, Gębka and Wohar (2013) suggest that a synchronous movement of a subset of investors into a subset of assets/markets could lead to increased return dispersion across the entire portfolio as the sum of the subsets.

Empirical studies on herding and contrarianism have mostly concentrated on detecting the existence of the behaviours with two broad approaches. One focuses on examining herding activities among certain groups of investors (i.e. institutional investors) using detailed records of trading activity (see, for example, Lakonishok et al. 1992). The other, less data-intensive approach, detects herding by analysing price movements towards the market average using aggregate market data (see Christie and Huang 1995 and Chang et al. 2000 among others).

Studies of herding in REITs often adopt the latter approach. Zhou and Anderson (2013) provide evidence of reverse herding (contrarianism) in the overall U.S. equity REITs market and in lower quantiles but identify herding in quantiles with significant price movements. These findings are consistent when the market is segmented into up and down days. Similarly, Philippas et al. (2013) detect herding behavior in U.S. equity REITs during 2004–2009 but find evidence of contrarianism in the period from 2009 to 2011. Babalos et al. (2015) find no significant herding in the overall equity REITs market but identify both herding and reverse herding in specific sub-sectors and under varying market regimes. Comparable findings are reported by Akinsomi et al. (2018) in the U.K. REITs market. Lesame et al. (2024) reveal that herding in international REITs is mainly driven by herding behaviour in developed market REITs. Our first set of hypotheses therefore are:

Hypothesis 1: Herding or contrarianism effects are significant within the entire equity REITs asset class.

Hypothesis 2: Herding or contrarianism effects are significant at the sub-sector level.

Notably, much of the existing literature focuses on detecting herding behavior, with limited exploration of the underlying drivers. For instance, Philippas et al. (2013) highlight the impact of investor sentiment and macroeconomic shocks on herding but primarily assess these variables through their influence on return dispersion rather than directly on herding itself. Zhou and Anderson (2013) propose that intentional herding is more likely during periods of market turmoil, while in calmer markets, 'investors will place more emphasis on market fundamentals than what the rational asset pricing models suggest' (Zhou and Anderson 2013, p. 86). However, the specific nature of these 'fundamentals' within the REIT sector remains unclear. Furthermore, the detection of contrarianism in the REITs market is often interpreted as 'no evidence of herding' (Akinsomi et al. 2018; Babalos et al. 2015; Philippas et al. 2013; Zhou and Anderson 2013), with limited analysis of the behaviour itself. As noted, contrarianism can also contribute to price distortion and market volatility and should not be overlooked when investigating investor behavior. Understanding contrarianism is crucial, as it plays a significant role in shaping market dynamics alongside herding tendencies.

2.2 The inherent characteristics of REITs and exogenous information signals

REITs are widely recognised for their distinctive combination of fixed-income and stock characteristics. In the short term, REITs resemble small stocks and bonds in terms of return and risk exposure (Hsieh and Peterson 2000). Over the long run, they assemble direct real estate assets (Clayton and MacKinnon 2003; Geltner 1998). It is possible that this inherent duality creates unique dynamics, where both equity and bond market factors shape investor behaviour.

Finance studies have found evidence of herding in small-cap stocks due to limited public information availability (Lakonishok et al. 1992; Wylie 2005), while institutional herding in corporate bonds is often linked to safety-seeking behaviour during economic uncertainty (Cai et al. 2019). In real estate, some evidence of herding exists in the housing market (Ngene et al. 2017), but there is a scarcity of evidence of herding/contrarianism in the commercial sector. Furthermore, in the cryptocurrency market, reverse herding (contrarianism) is observed across all sectors, except in cryptocurrencies backed by real estate assets, where neither herding or contrarianism is evident (Zhao et al. 2022). In light of the existing literature, we propose the following hypothesis:

Hypothesis 3: Herding or contrarianism effects are significant in REITs return series due to stock market fundamentals and those of fixed-income assets.

Externally, investment behavior is often influenced by signals derived from exogenous information flows (Philippas et al. 2020). Information cascades occur when investors observe the outcome of the previous decision-makers, they may follow such decisions and ignore their own private judgments (Banerjee 1992; Bikchandani et al. 1992; Welch 2000; Hirshleifer and Hong Teoh 2003). Avery and Zemsky (1998) show that informational cascade-induced herding is only possible if the market is uncertain about whether asset value has deviated from its initial expected value. This uncertainty, coupled with the ambiguity around the average accuracy of traders' information[2], could result in uninformative herd behaviour, ultimately causing significant impacts on prices.

[2] As argued by Yang (2011), it may be difficult for investors to distinguish between predecessors who made decisions based on their own private signals and those who are free riders on the costly signal acquisition.

Park and Sabourian (2011) and Park and Sgroi (2012) expanded models in Avery and Zemsky (1998) by incorporating multiple possible liquidation values for assets and multiple possible signals (for example, high, middle and low values and signals). They demonstrate that herding behaviour can emerge among traders who believe that extreme outcomes (such as significant price rises or falls) are more probable than moderate ones. Contrarily, contrarianism can arise among traders who hold the belief that moderate outcomes are more likely. The authors categorise these signals as 'volatility signals' and 'hill-shaped signals'[3], and the experiment in Park and Sgroi (2012) confirms these hypotheses.

REITs research has shown that private information affects the liquidity of the market (Danielsen and Harrison 2000), which traditionally suffered from low transparency and information asymmetry[4]. REIT investors may interpret informational signals from seemingly related markets, such as the stock and bond markets. These signals often start as spillovers but can evolve into collective signals that drive irrational behaviour (Philippas et al. 2020).

Such signals may also originate within the REITs market itself. For example, existing studies have found that larger firms tend to exhibit return patterns that lead those of smaller firms (Lo and MacKinlay 1990; Hou 2007). Lin et al. (2010) demonstrate that overconfidence[5] is more evident among large REITs compared to smaller ones. Recent research by Feng and Liu (2023) highlights that REITs focused on property rentals are less likely to take risks and more likely to achieve higher operational performance. Furthermore, Gyamfi-Yeboah et al. (2012) find that US REITs' Funds from Operations (FFO) announcements convey pricing information. Therefore, REITs investors may derive information from the performance of 'representatives' (i.e., the largest by market capitalisation, those with the greatest direct real estate allocation, or those with the best operational performance relative to total assets) and base their investment decisions on these indicators.

Based on the existing theoretical framework (Park and Sabourian 2011; Park and Sgroi 2012), our models examine if such signals intensify or reduce herding or contrarianism behaviours. Our last hypothesis therefore is:

Hypothesis 4: Informational signals from other markets and REITs representatives change the intensity of herding or contrarianism behaviours.

3 Methodology

3.1 Basis of the estimated model for herd behaviour

Rational asset pricing models suggest that stock return dispersion increases as market returns rise (Christie and Huang 1995). However, the presence of herding or contrarianism may cause stock returns to deviate from this expected relationship. Following Chang et al. (2000), we employ the cross-sectional absolute standard deviation (CSAD) as a measure to quantify return dispersion:

[3] Details on the signals are discussed in Section 3.

[4] Although the transparency of REITs has notably improved due to the increasing institutional holding (Ghosh and Sirmans 2006) and the reduced information asymmetry.

[5] As discussed above, overconfidence could result in contrarian behaviour.

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

Where $R_{i,t}$ is the observed daily return for REIT i at time t; $R_{m,t}$ is the equal-weighted average of all returns in our sample at time t; and N is the number of REITs included in the market portfolio at time t.

Chang et al. (2000) argue that if market participants either herd or trade against the market consensus, the relationship between return dispersion and market return may become nonlinear. To investigate this, the authors examine the potential nonlinear relationship between CSAD and $R_{m,t}$ as specified in Eq. 2. Under the Capital Asset Pricing Model (CAPM), the relationship between CSAD and $R_{m,t}$ is expected to be linear and increasingly positive. This occurs because individual asset returns exhibit greater dispersion in response to market movements due to heterogeneity in their market betas, resulting in a positive γ_1.[6]

To test herd/contrarian behaviour, the coefficient γ_2 is examined. A significantly negative γ_2 would indicate reduced dispersion, suggesting that market participants herd and deviate from the predictions of the CAPM. In contrast, a significantly positive γ_2 would indicate contrarian behaviour, where participants actively trade against the market consensus.

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

Herding and contrarianism within REIT sub-sectors have been identified in studies such as Philippas et al. (2013) and Essa and Giouvris (2023). One possible explanation for herding at the sub-sector level is localised herding or style investing within specific sub-sectors, as discussed by Gębka and Wohar (2013). To explore this further, we apply Eq. 2 at the REIT sub-sector level. If localised herding is present, γ_2 is expected to be significantly negative. Conversely, a significantly positive γ_2 would indicate contrarian behaviour within the sub-sector.

Equation 2 may be prone to issues such as high multicollinearity between the explanatory variables $R_{m,t}$ and $R_{m,t}^2$, as well as significant serial correlation commonly observed in high-frequency time series market data. To address these potential issues, and following the approach of Yao et al. (2014), we perform a robustness check by replacing $R_{m,t}^2$ in Eq. 2 with $(R_{m,t} - \bar{R}_m)^2$ and incorporating a 1-day lag of the dependent variable:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t} - \bar{R}_m)^2 + \gamma_3 CSAD_{t-1} + \varepsilon_t \tag{3}$$

Where $\bar{R}_m$ is the arithmetic mean of $R_{m,t}$ and $CSAD_{t-1}$ is the 1-day lag of CSAD. Again, a negative/positive and statistically significant γ_2 indicates the presence of herding/contrarianism.

We also incorporate several time-varying approaches to enhance robustness. These include a combination of an autoregressive (AR) term with a GARCH model (Ballis and Drakos 2020; Tan et al. 2008) and a one-year rolling window analysis (Bouri et al. 2019; Clements et al. 2017; Stavroyiannis and Vassilios 2017; Zhao et al. 2022).

Extreme outliers can have a substantial impact on the tail values of a distribution, yet such information may be overlooked in OLS models, as least squares estimators focus pri-

[6] This is demonstrated in the Appendix.

marily on the mean as a measure of central tendency (Chiang et al. 2010). To address this limitation, and following the methodology of Chiang et al. (2010) and others, we employ quantile regression to examine the relationship between CSAD and $R^2_{m,t}$ at the 75th, 50th, and 25th quantiles, respectively:

$$CSAD_{\tau,t} = \alpha + \gamma_{1,\tau} R_{m,t} + \gamma_{2,\tau} R^2_{m,t} + \varepsilon_{\tau,t} \tag{4}$$

Where τ represents a specific quantile.

3.2 Stock vs fixed-income

REITs exhibit characteristics that combine elements of both stocks and bonds in terms of risk exposure (Clayton and MacKinnon 2003; MacGregor et al. 2021), while their income streams are directly tied to real estate performance. Following Hsieh and Peterson (2000), we decompose these inherent characteristics of REIT returns into stock and fixed-income components using Eq. 5. Here, $MKTRF_t$ represents the excess return of a value-weighted market portfolio comprising NYSE, Amex, and NASDAQ stocks; SMB_t and HML_t are the size (small minus big) and value-growth (high minus low) factors, respectively; RMW_t and CMA_t are the profitability (robust minus weak) and investment (conservative minus aggressive) factors introduced by Fama and French (2015); and MOM_t is the momentum factor from Carhart (1997). All factor data were sourced from Kenneth French's data library.

$$\begin{aligned} R_{i,t} - R_{F,t} = \alpha + \beta_{mkt,i} MKTRF_t + \beta_{smb,i} SMB_t + \beta_{hml,i} HML_t \\ + \beta_{rmw,i} RMW_t + \beta_{cma,i} CMA_t + \beta_{mom,i} MOM_t + \varepsilon_t \end{aligned} \tag{5}$$

To isolate the variations in equity REIT returns that are independent of the stock market factors described above, we construct an orthogonalised fixed-income factor (encompassing both real estate and bond-like characteristics). This factor is defined as the sum of the intercept, the error terms from Eq. 5, and the risk-free rate $R_{F,t}$. The portion of the return attributed to the stock market is calculated as the sum of the products of risk factors and their corresponding sensitivities.[7] Dividing REIT returns into these two components allows us to compute two separate CSAD series: $CSAD_{stock,t}$ and $CSAD_{fixed-income,t}$, using Eq. 1, we obtain:

$$CSAD_{stock,t} = \alpha + \gamma_{1,stock} |R_{m,t}| + \gamma_{2,stock} R^2_{m,t} + \varepsilon_t \tag{6}$$

$$CSAD_{fixed-income,t} = \alpha + \gamma_{1,fixed-income} |R_{m,t}| + \gamma_{2,fixed-income} R^2_{m,t} + \varepsilon_t \tag{7}$$

To determine whether herding or contrarianism is specific to the inherent characteristics of REITs, we examine the sign and significance of $\gamma_{2,stock}$ and $\gamma_{2,fixed-income}$. Notably, our approach shares similarities with the works of Galariotis et al. (2015) and Ali et al. (2023), which utilise Fama-French common risk factors to decompose CSAD into compo-

[7] In this paper, we treat fixed-income factors as encompassing both direct real estate and bond-like securities. Since fixed-income factors are latent and not directly observable, the summation of the products of observed risk factors and their associated loadings represents the segment of REIT returns attributable to the stock market. The remaining components are interpreted as the fixed-income factor segment.

nents driven by reactions to fundamental information (spurious herding) and those driven by intentional herding. However, we contend that the Fama-French factor model, being an asset pricing model, is most appropriately applied at the return level. Applying the model directly to CSAD, as in Galariotis et al. (2015) and Ali et al. (2023), appears to lack a strong theoretical foundation.[8]

3.3 Informational signals and Herding

As discussed in Section 2, private information affects the liquidity of REITs market (Danielsen and Harrison 2000), which has traditionally been characterised by low transparency and high information asymmetry. REIT investors are likely to rely on exogenous private signals from other markets to inform their decision-making.

In Park and Sabourian (2011); Park and Sgroi (2012); Philippas et al. (2020), there are three possible liquidation values for each asset $V_1 < V_2 < V_3$ at the end of time t are defined, corresponding to the three possible states (low, middle and high). The information set is defined as $I = Pr(S_i|V_j)_{ij} = 1, 2, 3$, where $Pr(S_i|V_j)$ is the probability that an investor receives signal S_i given that the true value of the asset is V_j.

When signals are monotonically decreasing, such that $Pr(S|V_1) > Pr(S|V_2) > Pr(S|V_3)$, investors receiving low signals shift probability weight towards low asset values and are therefore more likely to sell. Conversely, when signals are monotonically increasing, with $Pr(S|V_1) < Pr(S|V_2) < Pr(S|V_3)$, investors receiving high signals shift probability weight towards high values and are more likely to buy. In the case of a U-shaped signal distribution, defined by $Pr(S|V_1) > Pr(S|V_2)$ and $Pr(S|V_2) < Pr(S|V_3)$, investors overweight extreme outcomes by adjusting their private expectations faster than prices, generating what Park and Sabourian (2011) describe as 'volatility signals'; such signals are a key condition for herd behaviour. By contrast, a hill-shaped signal distribution, where $Pr(S|V_1) < Pr(S|V_2)$ and $Pr(S|V_3) < Pr(S|V_2)$, leads investors to place greater weight on the middle value as expectations adjust more slowly than prices, encouraging contrarian behaviour.

Empirically, private signals are not directly observable. However, we can observe how the overall REITs market return responds to price movements and sentiment in other markets. Following Welch (2000), we use ex-post prices as a proxy for fundamental ex-ante information, positing that investors are likely to derive private signals from informational sources, including the stock market, bond market, within the REITs market itself, and the general market sentiment.

For the stock and bond market measures, we assess REITs returns relative to the daily prices of S&P 500, U.S. 3-month T-Bill, U.S. government bonds. As discussed in Section 2, investors may also derive insight from 'representative' REITs within the market. We define the top 33rd percentile of REITs based on market capitalisation[9], allocation in real estate assets, and FFO relative to total assets (Feng et al. 2022; Feng and Liu 2023) as proxies for such 'representative stocks' in the REITs market. Furthermore, building on the works of Balcilar et al. (2014); Economou et al. (2018), and Huang et al. (2020), we incorporate the Chicago Board Options Exchange (CBOE) VIX and the Economic Policy Uncertainty

[8] This argument can be further supported by comparing the $\hat{R}^2$ or empirical fit of factor models when regressed against returns versus CSAD.

[9] This approach is similar to Zhou and Anderson (2013), who use the largest 30%.

(EPU) index to derive signals. The CBOE VIX measures the implied volatility based on S&P 500 options, capturing investor expectations about future stock market volatility. The EPU index serves as a measure of market uncertainty. Both series are used as proxies for market sentiment.

The detailed definitions of these informational signals are presented in Appendix A.5. In essence, using the stock and bond markets as illustrative examples, informational signals are identified when prices in these markets fluctuate while REIT market returns are either positive or negative. In such cases, despite uncertainty in the stock or bond markets, the REIT market shifts probability weight towards either low or high valuation states in response to implicit informational signals. Informational signals may also arise when stock or bond market indicators suggest an optimistic (pessimistic) outlook, yet the REIT market does not incorporate this information and instead records negative (positive) returns. This divergence may reflect information asymmetry, leading to delays in the transmission of publicly available information to the REIT market. Alternatively, the presence of unobserved private information may induce REIT investors to shift probability weight towards extreme outcomes.

Last but not least, we include further measures on market conditions, including flight to safety (FTS) and major recession periods. FTS occurs when investors shift capital from more risky or more uncertain assets/markets into more secure ones during periods of high volatility and uncertainty. Gębka and Wohar (2013) assert that excess FTS may lead to contrarianism. As REITs are listed stocks, we use measures in Baele et al. (2020) and Boudry et al. (2022) to define FTS as a simultaneous occurrence of exceptionally high bond returns ($r_{b,t}$) and low stock returns ($r_{s,t}$) on a given day:

$$FTS_t = I\{r_{b,t} > z_b\} \times I\{r_{s,t} < z_s\} \tag{8}$$

Where $I\{\cdot\}$ is the indicator of bivariate regime switching function, z_b is the threshold value for bond returns and estimated from $z_b = \kappa \cdot \sigma_{b,t}$, and z_b is the threshold value for stock returns and estimated from $z_s = -\kappa \cdot \sigma_{s,t}$. $\sigma_{b,t}$ and $\sigma_{s,t}$ are the past 22-day rolling return volatility ($t-1$ to $t-22$), and $\kappa = 1.5$ (Baele et al. 2020; Boudry et al. 2022).

Following Philippas et al. (2013); Cai and Xu (2022); Chong and Phillips (2022), we incorporate recession periods identified by the National Bureau of Economic Research (NBER) into our models to assess the impact of severe economic shocks on investment behaviours. These periods include the high inflation and tight monetary policy of the early 1980s, the oil price shock and real estate and credit crises of the early 1990s, the bursting of the Dot-Com bubble in the early 2000s, the Global Financial Crisis (GFC) between 2007 and 2009, and the onset of the COVID-19 pandemic.

The GFC is also examined separately, given its origin in the real estate debt crisis. Prior research shows that the GFC substantially weakened REIT liquidity (Devos et al. 2014), reduced the diversification benefits traditionally associated with REITs (Lu et al. 2013), and resulted in significant underperformance and heightened risk during the crisis period (Newell and Peng 2009).

Building on the above, for simplicity, we use γ_{signal} as a composite coefficient associated with the set of variables *X*, capturing the indicator days *D*, on which informational signals, FTS episodes, or recession periods are present. In our linear regression analysis, we examine the impact of these signals and periods on herding and contrarian behaviours:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_{signal} D_{signal,t}^X R_{m,t}^2 + \varepsilon_t \tag{9}$$

γ_{signal} is compared with γ_2 to see if signals or FTS/recession periods amply or dampen herding/contrarianism. For instance, in a situation where γ_2 is significantly positive (negative), a significantly positive (negative) γ_{signal} implies that contrarianism (herding) is amplified during the days where informational signals or FTS/recession are defined; by the same token, a significantly negative (positive) γ_{signal} implies that contrarianism (herding) behaviour is dampened by the signals. If γ_2 is statistically insignificant, but γ_{signal} is significantly positive (negative), the model would suggest that REITs market exhibits contrarianism (herding) behaviours as a result of the signals or FTS. An insignificant γ_{signal} implies that informational signals or FTS have little impact on the asset pricing model.

4 Data

We utilise the daily data of equity REITs from 02 January 1980 to 31 December 2021, sourced from the survivor bias-free CRSP Ziman REITs database. This dataset covers sectors including diversified, healthcare, industrial/office, lodging, residential, retail, self-storage, and others.[10] Daily frequency data is employed to analyse REIT investors' responses to informational signals over recent days. Higher-level frequencies, such as monthly or quarterly data, would not sufficiently capture such short-term reactions.[11]

Figure 1 illustrates the market growth of U.S. equity REITs, showing an increase in the number of equity REITs from 35 in 1980 to 175 in 2021, alongside market capitalisation growth from 0.9 billion to 1.65 trillion. The early 1990s witnessed a 'REIT boom', characterised by significant growth in numbers (Clayton and MacKinnon 2003).

Table 1 presents descriptive statistics for daily market returns, CSAD, and the correlation matrix among REIT sectors. The top panel shows that, on average, all REIT sectors yield positive daily returns. The mean daily return ranges from a high of 0.000869 for the 'Others' category to a low of 0.000633 for Retail REITs. Among the sectors, the Lodging sector exhibits the highest volatility, while the Residential sector demonstrates the lowest volatility.

Regarding CSADs, the Lodging sector also shows the greatest return dispersion, indicating higher variability among individual REIT returns within the sector. In contrast, Self-storage REITs display greater cross-sectional similarity, suggesting tighter clustering of returns. These observations highlight the variability in return dynamics across sectors.

The return correlation matrix, shown in the bottom panel of Table 1, reveals that daily returns among all sectors are positively correlated at the 1% significance level. However, the 'Others' category exhibits relatively weaker correlations with all other sectors. Similarly, weaker correlations are observed between the Lodging and Self-storage sectors. These variations in correlations and volatility likely reflect sector-specific exposures to macroeconomic factors or differing responses to market-wide events. This variability underscores the importance of examining how external informational signals influence behavioral tendencies.

[10] "Others" include the combined unknown and mortgage sectors.

[11] Nevertheless, we applied Eqs. 1 to 7 to monthly data for robustness check, the results are shown in the Appendix.

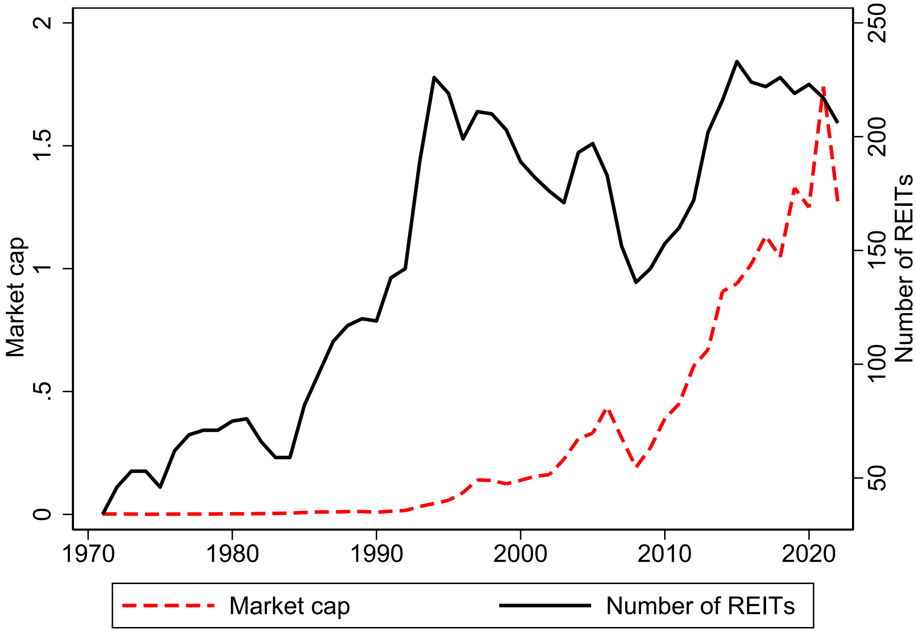


Fig. 1 U.S. Equity REITs market overview: the figure presents the number and market capitalisation (in trillions \$) of U.S. equity REITs during 1980-2021, quoted from NAREIT

To derive signals, we utilise daily data on S&P 500 prices, U.S. Treasury bills (T-bills), and U.S. Treasury bond prices to represent the general stock and bond markets. As outlined in Section 3, we also incorporate the CBOE VIX and EPU indices as proxies for market sentiment and uncertainty. Additionally, we use the prices of the top 33rd percentile of REITs, ranked by market capitalisation, the proportion of real estate asset allocation in their portfolios, and FFO relative to total assets, as 'representative' REITs. Other critical periods include FTS defined as in Eq. 8 and recession periods defined by the NBER.

5 Empirical results

5.1 Herding and contrarianism

The results of Eqs. 2, 3, 4, and additional robustness checks are summarised in Table 2. Consistent with the CAPM specification, the estimated γ_1 is positive and statistically significant across all models. Except for the rolling window specification, all models produce positive and significant γ_2 estimates, aligning with previous findings of contrarianism in static models (Philippas et al. 2013; Zhou and Anderson 2013). Notably, unlike Zhou and Anderson (2013), who report contrarianism primarily in the low-to-middle quantiles of the return dispersion distribution, our quantile regression results show positive γ_2 estimates across all three quantiles. This indicates that contrarian behaviour is more pervasive and not confined to specific parts of the distribution.

Table 1 U.S. Equity REITs Market: the number of REITs (n), the mean, maximum, minimum and standard deviation of market returns of equal-weighted portfolio ($\bar{R}_m$, R_m^{max}, R_m^{min}, σ_{rm}), and CSAD ($\overline{CSAD}$, $CSAD^{max}$, $CSAD^{min}$, σ_{CSAD}) (computed from Eq. 1), and correlation matrix (all significant at 1%) for Equity REITs during 1980-2021

	n	$\bar{R}_m$	R_m^{max}	R_m^{min}	σ_{Rm}	$\overline{CSAD}$	$CSAD^{max}$	$CSAD^{min}$	σ_{CSAD}
All	486	0.000696	0.1715	-0.1912	0.0126	0.012900	0.1282	0.0039	0.0068
Diversified	60	0.000674	0.1614	-0.1970	0.0136	0.014545	0.2902	0.0019	0.0104
Healthcare	31	0.000679	0.1970	-0.2424	0.0148	0.009207	0.1316	0.0000	0.0089
Industrial/Office	101	0.000747	0.1871	-0.2258	0.0144	0.014173	0.2185	0.0000	0.0107
Lodging	43	0.000724	0.3979	-0.2780	0.0221	0.016581	0.3730	0.0000	0.0182
Residential	74	0.000770	0.2629	-0.1898	0.0128	0.011647	0.3561	0.0007	0.0098
Retail	94	0.000633	0.2039	-0.2235	0.0144	0.011190	0.1218	0.0012	0.0066
Self-storage	27	0.000706	0.1651	-0.1818	0.0154	0.005592	0.0822	0.0000	0.0056
Others	56	0.000869	0.2516	-0.1578	0.0179	0.015607	0.4342	0.0000	0.0200
	All	Divers	Health	Indu/Office	Lodging	Resid	Retail	Storage	Others
All	1								
Diversified	0.8549	1							
Healthcare	0.8159	0.6692	1						
Industrial/Office	0.9005	0.7339	0.6987	1					
Lodging	0.7147	0.5727	0.5534	0.5753	1				
Residential	0.8511	0.6942	0.6836	0.7311	0.5333	1			
Retail	0.938	0.7753	0.7572	0.7992	0.6452	0.7641	1		
Self-storage	0.7069	0.5805	0.5780	0.6473	0.4479	0.6072	0.6534	1	
Others	0.6142	0.4603	0.4801	0.4997	0.3757	0.4784	0.5276	0.4137	1

Table 2 Model robustness check: model specifications consist of OLS estimation of Eq. 2 (OLS), linear model with additional autoregressive and heteroskedasticity terms (OLS+AR+GARCH), OLS under rolling window context (the average presented), and other model specifications in Eqs. 3 and 4 for the period 1980-2021 for all U.S. Equity REITs

	OLS	OLS+AR+GARCH	Rolling OLS	Yao et al. (2014)	Quantile		
					25%	50%	75%
	Daily						
γ_1	0.2383***	0.1636***	0.3055***	0.0997***	0.0801***	0.0893***	0.2141***
γ_2	1.1811***	0.3123***	11.11	0.8069***	2.3831***	2.7253***	2.0997***
α	0.0111***	0.0106***	0.0108***	0.0026***	0.0079***	0.0104***	0.0135***
$\gamma_{CSAD,t-1}$		0.9407***		0.7345***			
$ARCH$		0.1086***					
$GARCH$		0.8653***					
Loglikeihood		45139.05					
$Adj - R^2$	28.41%		37.33%	75.90%	5.90%	7.32%	10.91%
T	10592	10592	10592	10592	10592	10592	10592

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The t-statistics are computed using Newey-West HAC robust standard errors

To investigate results from the rolling window estimation further, we plot the time-varying t-statistics of γ_2 in the rolling window specification against the 95% critical values (illustrated by the two horizontal dashed lines) in Fig. 2. Relatively short periods of herding are observed in the early 1980s and mid-1990s, and early 2020. Extended and frequent periods of contrarianism are evident throughout the time period. Examining the major U.S. recession periods highlighted in the graph, investors not only demonstrate contrarian behaviour during recessions in the 80s, early 2000s, the GFC in 2007, and the beginning of the Covid period, but also exhibit prolonged contrarianism between these recessionary periods. The impact of recessionary periods is examined in greater detail later in this section.

Notably, these results differ somewhat from those of Zhou and Anderson (2013), who suggest that herding is more likely to occur and becomes stronger in declining markets than in rising markets. There are two key points to consider: first, while contrarianism is also observed in down markets in Zhou and Anderson (2013), it is interpreted as 'no evidence of herding'. Second, this discrepancy may stem from methodological differences. Specifically, Zhou and Anderson (2013) classify up and down markets based on REITs' overall returns, with negative returns defined as declining markets and positive returns as rising markets. In contrast, Fig. 2 examines herding and contrarianism within the broader context of NBER-defined recessions.

As discussed in Section 2, one possible reason for contrarianism is localised herding or style investing, as investors move in and out of the sub-sector, the prices of the subset of assets increase or decrease, leading to increased CSAD measures across the entire market (Gębka and Wohar 2013). We repeat Model 2 at the sub-sector level, and the OLS results are shown in Panel (a) in Table 3. Consistent with Philippas et al. (2013) and Essa and Giouvris (2023), our results also indicate localised herding in certain REITs sectors such as Healthcare and Industrial/Office. However, contrarianism is also observed in Residential (marginally significant), Retail, Self-storage, and 'Others' sectors.

The rolling window results by REITs sector are presented in Fig. 3. Consistent with the aggregate-market evidence shown in Fig. 2, the sector-level results reveal only sporadic

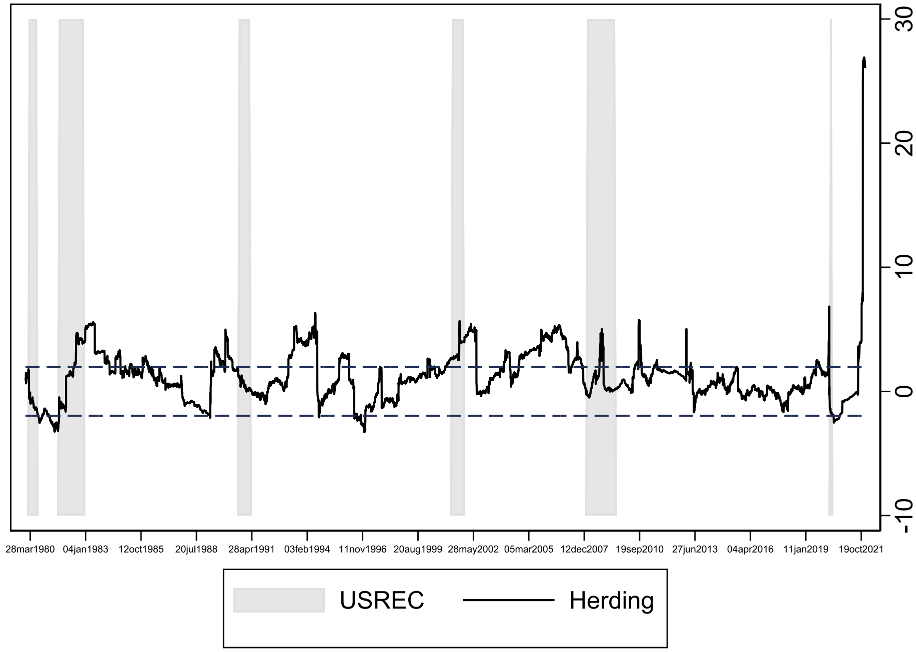


Fig. 2 The t-statistics of estimated γ_2 from the rolling window estimation: the figure presents the t-statistics of γ_2 in Eq. 2 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows

and short-lived episodes of herding, contrasted with more extended, recurrent, and often consecutive periods of contrarian behaviour across most REIT sectors. This pattern suggests that, at the sector level, investors more frequently diverge in their responses to large market movements rather than converge on a common trading direction. Importantly, the timing, duration, and intensity of both herding and contrarianism vary considerably across sectors, with little synchronisation in their occurrence. Such heterogeneity implies meaningful behavioural differences across REIT sub-sectors, likely driven by sectoral variations in information transparency, asset heterogeneity, tenant composition, and sensitivity to macroeconomic and real estate specific shocks.

The rolling-window results confirm the presence of both herding and contrarian behaviour, as posited in Hypotheses 1 and 2, with contrarianism emerging as the dominant phenomenon in the REIT return series.

5.2 Inherent characteristics of REITs and Herding/contrarianism

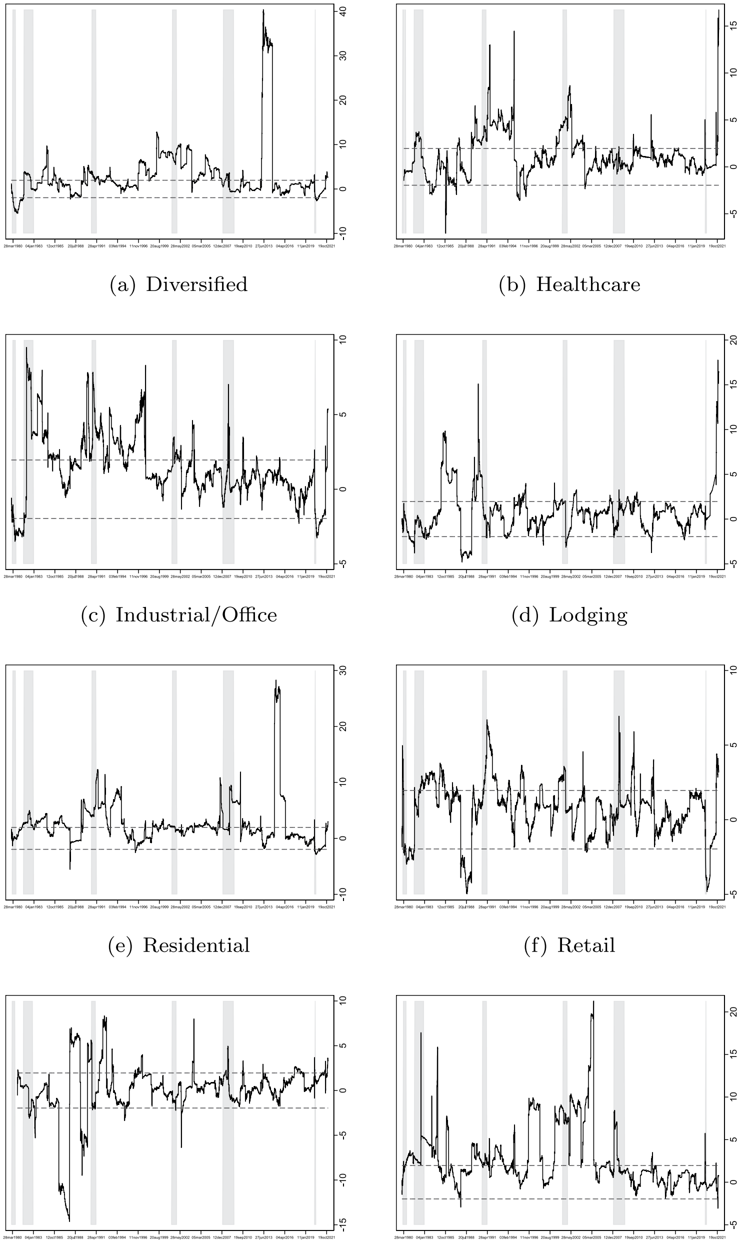
In Eqs. 6 and 7, we decompose the inherent characteristics of REIT returns into stock and fixed-income components and calculate two separate CSAD series. We then apply the baseline model and the rolling window model to each series. The results are presented in Panels (b) and (c) of Table 3 and rolling window results are illustrated in Fig. 4[12].

[12] Rolling window results for each sector are also shown in Appendix Figs. 9, and 10.

Table 3 Linear regression results by sectors, $CSAD_{stock}$ and $CSAD_{fixed-income}$: the table presents the estimated coefficients and associated t-statistics of Eq. 2, estimated from OLS regression with Newey-West HAC robust standard errors for the period 1980-2021 for different property sectors of U.S. Equity REITs

	All	Diversified	Healthcare	Industrial/Office	Lodging	Residential	Retail	Self-storage	Others
		Panel (a): OLS of All							
γ_1	0.2383***	0.5689***	0.3679***	0.5127***	0.7654***	0.4457***	0.2650***	0.0512***	0.6918***
γ_2	1.1811***	-0.1521	-0.6037**	-1.1166***	-0.3265	1.9346*	0.6676***	0.8282***	3.7496***
α	0.0111***	0.0099***	0.0060***	0.0101***	0.0072***	0.0080***	0.0090***	0.0049***	0.0075***
$Adj-R^2$	28.41%	34.06%	18.41%	21.15%	53.16%	41.38%	36.45%	6.51%	67.10%
T	10592	10592	10592	10592	10592	10592	10592	10368	10592
		Panel (b): OLS of Stock CSAD							
γ_1	0.3644***	0.3629***	0.1468***	0.2172***	0.2122***	0.2284***	0.1741***	0.1242***	0.2877***
γ_2	0.0789	-0.3014*	-0.1594**	-0.0497*	-0.1021*	-0.2889	0.0980	0.2020	-0.5514***
α	0.0028***	0.0009***	0.0005***	0.0011***	0.0017***	0.0007***	0.0007***	0.0004***	0.0011***
$Adj-R^2$	55.70%	85.22%	59.80%	69.12%	80.72%	72.62%	81.11%	45.18%	60.02%
T	10592	10592	10592	10592	10592	10592	10592	10368	10592
		Panel (c): OLS of Fixed-income CSAD							
γ_1	0.5428***	0.6357***	0.3265***	0.7126***	0.9475***	0.6895***	0.2080***	0.0398***	1.0396***
γ_2	0.9685***	6.5259***	3.2963***	0.8957	0.7796*	3.7042***	5.7308***	0.5751***	2.9024***
α	0.0112***	0.0100***	0.0064***	0.0095***	0.0071***	0.0071***	0.0095***	0.0060***	0.0064***
$Adj-R^2$	56.78%	45.63%	19.42%	26.64%	63.53%	52.05%	23.03%	1.50%	78.73%
T	10592	10592	10592	10592	10592	10592	10592	10368	10592

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$



(a) Diversified

(b) Healthcare

(c) Industrial/Office

(d) Lodging

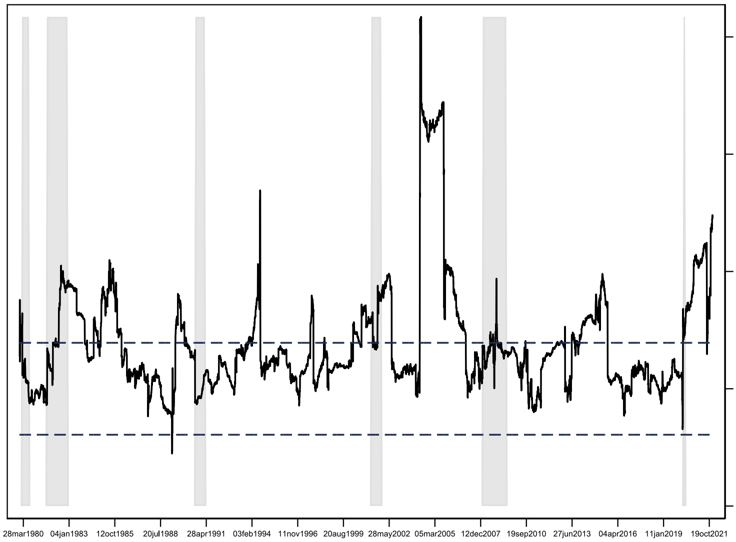
(e) Residential

(f) Retail

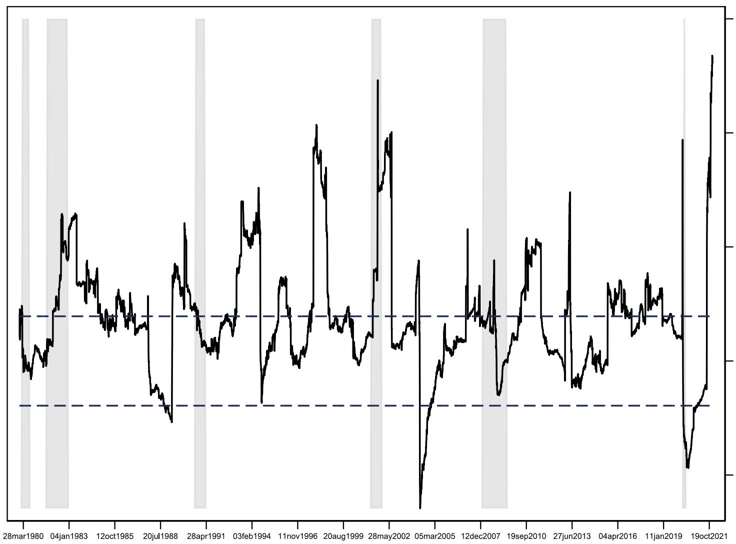
(g) Self-storage

(h) Others

Fig. 3 The t-statistics of γ_2 from the rolling window estimation: the figure presents the t-statistics of estimated γ_2 in Eq. 2 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) Stock CSAD



(b) Fix-income CSAD

Fig. 4 The t-statistics of γ_2 from the rolling window estimation: $CSAD_{stock}$ vs $CSAD_{fixed-income}$: the figure presents the t-statistics of estimated γ_2 in Eq. 2 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows

The OLS results in Table 3 reveal that for the entire REIT sector, γ_2 is insignificant in the $CSAD_{stock}$ specification but significantly positive in the $CSAD_{fixed-income}$ specification, indicating that contrarianism is predominantly associated with the fixed-income characteristics of REITs. To further explore these dynamics, we focus our narrative on the rolling window results illustrated in Fig. 4.

The rolling window analysis reveals that investors predominantly trade against the market consensus, drawing on both stock and fixed-income information. In contrast, evidence of herding is relatively limited and episodic. As shown in Panel (a), only a single brief episode of statistically significant herding is observed in 1988, indicated by a negative and significant γ_2 coefficient for the $CSAD_{stock}$ series. Similarly, Panel (b) reveals just three relatively short-lived herding episodes in the $CSAD_{fixed\text{-}income}$ series, occurring in 1988, 2004/2005, and 2020.

Notably, the herding episode in 2004/2005 in the $CSAD_{fixed\text{-}income}$ series coincides with a period of rapid property price appreciation and substantial capital inflows into real estate markets, implying that investors increasingly relied on common valuation signals and credit-market conditions, thereby reinforcing correlated trading behaviour. By contrast, during the subsequent GFC, both the $CSAD_{stock}$ and $CSAD_{fixed\text{-}income}$ series exhibit pronounced contrarianism, suggesting that REIT investors actively traded against prevailing market trends in response to heightened uncertainty, liquidity constraints, and divergent assessments of asset fundamentals. This behaviour is consistent with investors reassessing risk and value in stressed conditions (Ozcelebi and Yoon 2025), rather than mechanically following market movements.

Referring back to Hypothesis 3, our results indicate a predominance of contrarian behaviour in REIT returns that can be attributed to their hybrid nature, encompassing both equity- and bond-like characteristics. However, the timing of contrarian episodes differs markedly across the $CSAD_{stock}$ and $CSAD_{fixed-income}$ series, with periods of contrarianism in one market not necessarily coinciding with contrarian behaviour in the other. This lack of temporal alignment suggests that REIT investors process and respond to information from equity and fixed-income markets in a non-synchronous manner, selectively weighting market-specific signals depending on prevailing conditions. These results imply that the interaction between asset-specific fundamentals and cross-market information flows plays a crucial role in shaping investor behaviour, contributing to the complex, heterogeneous, and time-varying dynamics observed in REIT returns (Clayton and MacKinnon 2003).

When exploring sector variances, the estimated coefficients using the OLS specification (see Table 3) show that on average, localised herding in the Diversified, Healthcare, Industrial/office, Lodging, and ‘Others’ sectors is associated with the stock characteristics of REITs, whereas contrarianism in all sectors except Industrial/office, is linked with the fixed-income characteristics of REITs. Results from the rolling windows estimation[13] resemble those presented previously, that more frequent periods of contrarian behaviour are observable in all sectors. This pattern persists irrespective of whether return dispersion is measured against stock market fundamentals or fixed-income assets.

[13] See Appendix A.4.

5.3 Signals and herding/contrarianism

The results of signals derived from the stock market, bond market, market sentiment, REIT 'representatives', and critical periods are presented in Table 4. Panel (a) provides the OLS results using overall CSAD, while Panels (b) and (c) present results for $CSAD_{stock}$ and $CSAD_{fixed-income}$, respectively. Panel (a) shows that consistent with previous results, both γ_1 and γ_2 are significantly positive. Signals from the stock and bond markets, REITs 'representatives', market sentiment, and recession periods have varying effects on the tendency of herding/contrarianism. As above, we focus our narrative on the rolling window results in Figs. 5–7, which display the t-statistics of the estimated γ_2 (solid lines) and γ_{signal} (red dotted lines).

In Fig. 5, Panel (a) shows that volatility signals from the general stock market (i.e., S&P 500) increase herding tendencies during and around most recessionary periods, consistent with the theoretical framework. However, during the 1980s and 1990s, when the REIT market was relatively immature and characterised by lower liquidity and limited institutional participation, stock market signals instead exhibit an 'amplifying' effect on contrarian behaviour. This suggests that investors responded heterogeneously to stock market information during this earlier phase of market development. This dynamic is also reflected in the overall insignificance of γ_{signal} in Table 4, highlighting the nuanced impact of stock market signals across different periods.

Examining the results in greater detail, Panel (b), which reports the rolling-window estimates for the $CSAD_{stock}$ series, shows prolonged periods of significantly positive γ_{signal} coefficients. This pattern indicates that volatility signals originating from the stock market encourage investors to place greater weight on private or stock-specific information, thereby amplifying dispersion in REIT returns linked to equity market fundamentals. In other words, stock market signals tend to strengthen contrarian behaviour within the equity-driven component of REIT pricing.

In contrast, Panel (c) which presents the corresponding results for the $CSAD_{fixed-income}$ series, reveals that γ_2 and γ_{signal} frequently carry opposing signs. This suggests that stock market signals act to dampen the reverse herding (contrarianism) associated with the fixed-income characteristics of REITs, partially offsetting dispersion that would otherwise arise from bond-market-related information. Taken together, these findings imply that stock market signals play an asymmetric role across the two dimensions of REIT pricing. Specifically, they amplify dispersion and contrarian behaviour when investors focus on equity-like fundamentals, while simultaneously mitigating contrarian tendencies linked to fixed-income characteristics. This asymmetry helps explain why herding effects identified in earlier studies may be context-dependent, arising from the interaction between stock market signals and the hybrid equity–bond nature of REITs.

Turning to signals derived from the bond market, including T-bills and U.S. government bond yields, we observe broadly similar effects (see columns 2 and 3 in Table 4). The significant and opposing signs of γ_2 and γ_{signal} in Panel (a) in Table 4) suggest a predominate 'dampening' effect from T-bill signals on both herding and contrarianism in the overall REIT market. This is further confirmed in the rolling window estimates shown in Panel (a) of Fig. 6.

Focusing specifically on T-bill signals, Panel (b) of Fig. 6, which reports the rolling-window estimates for the $CSAD_{stock}$ series, shows that periods of significant γ_{signal} coef-

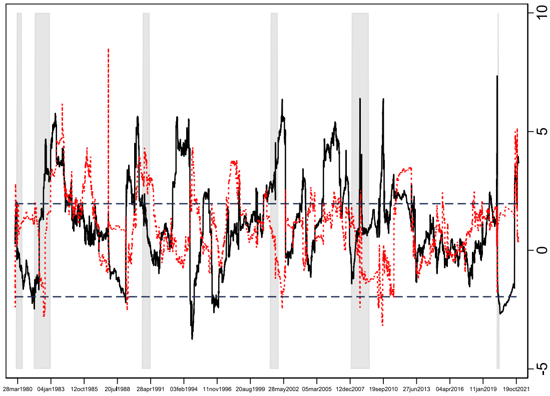
Table 4 Linear regression results with signals and recession periods: the table presents the estimated coefficients and t-statistics of Eq. 2, using OLS regression with Newey-West HAC robust standard errors for the period 1980-2021 for different property sectors of U.S. Equity REITs

	SP500	Tbill	US Gov Bond	CBOE VIX	EPU	Size	RE/TA	FFO/TA	FTS	GFC	NBER
Panel (a): OLS of All											
γ_1	0.2367***	0.2365***	0.2368***	0.2229***	0.2028***	0.2378***	0.2383***	0.2374***	0.2081***	0.2391***	0.2495***
γ_2	1.2840***	1.6608***	1.5925***	1.0772***	1.0518***	0.9573***	0.9748***	0.9362***	1.8556***	1.0458***	0.5883***
γ_{Signal}	-0.1216	-0.5839*	-0.5054*	0.3856*	0.5310	0.3800	0.3362	0.4156	-1.5602***	0.1943*	0.5372***
α	0.0111***	0.0111***	0.0111***	0.0109***	0.0115***	0.0111***	0.0111***	0.0111***	0.0112***	0.0111***	0.0111***
$Adj-R^2$	28.42%	28.54%	28.51%	30.26%	27.73%	28.49%	28.47%	28.50%	29.41%	28.43%	28.45%
T	10592	10592	10592	8064	9327	10592	10592	10592	10592	10592	10592
Panel (b): OLS of Stock CSAD											
γ_1	0.3723***	0.3633***	0.3630***	0.3367***	0.3492***	0.3639***	0.3644***	0.3637***	0.3563***	0.3663***	0.3814***
γ_2	-0.4392*	0.3730	0.4791*	-0.0517	0.0019	-0.1268	-0.1781	-0.1084	0.2597*	-0.2194*	-0.8129***
γ_{Signal}	0.6121***	-0.3579	-0.4915*	0.5261***	0.2514*	0.3494*	0.4190***	0.3181*	-0.4182*	0.4285***	0.8082***
α	0.0027***	0.0028***	0.0028***	0.0032***	0.0030***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***	0.0027***
Panel (c): OLS of Fixed-income CSAD											
γ_1	0.5318***	0.5432***	0.5435***	0.5291***	0.5132***	0.5429***	0.5428***	0.5429***	0.5343***	0.5418***	0.5394***
γ_2	1.6891***	0.8579***	0.7740***	1.3994***	1.1194***	1.0364***	1.1404***	1.0111***	1.1583***	1.1199**	1.1482***
γ_{Signal}	-0.8513***	0.1346	0.2388*	-0.4956*	0.0902	-0.1154	-0.2803	-0.0723	-0.4391	-0.2175**	-0.1629
α	0.0112***	0.0112***	0.0112***	0.0111***	0.0116***	0.0112***	0.0112***	0.0112***	0.0112***	0.0112***	0.0112***

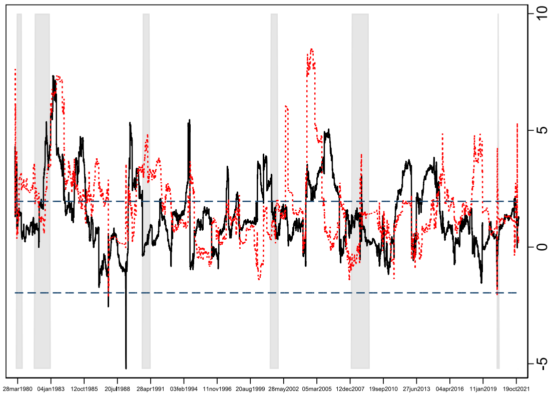
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Signals are derived from the daily prices of S&P500, US 3-month T-Bill, US government bonds; index values from CBOE VIX and EPU, daily prices of 'Representative' REITs based on market cap, proportion of real estate assets (RE/TA), funds from operations on assets (FFO/TA), defined FTS periods using Eq. 8, and GFC and NBER crisis periods

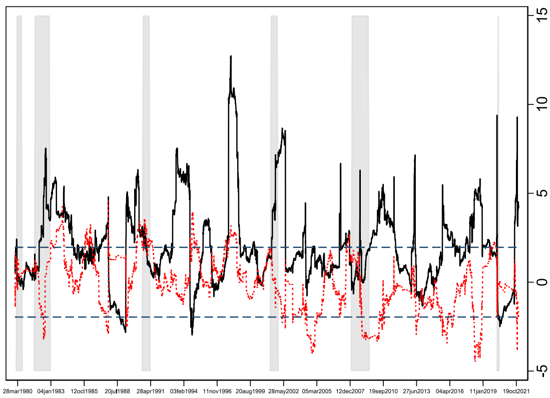
Fig. 5 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signals from S&P500: the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD

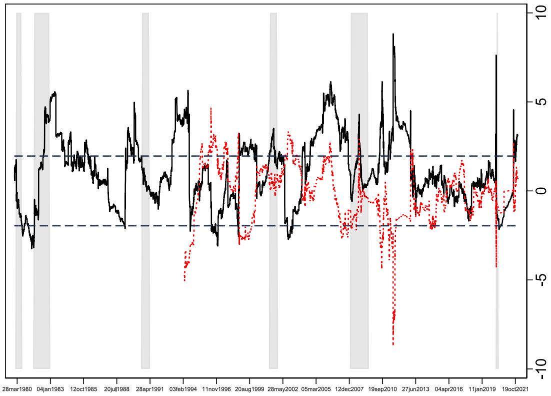


(b) Stock CSAD

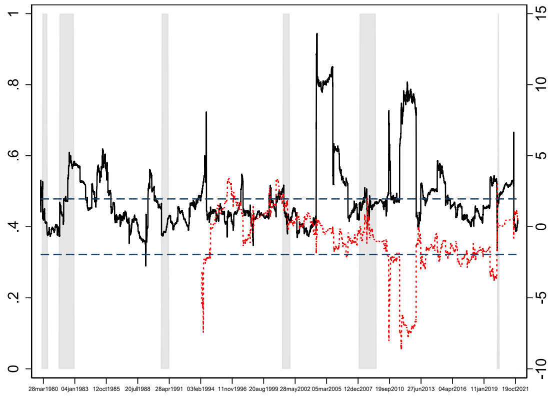


(c) Fix-income CSAD

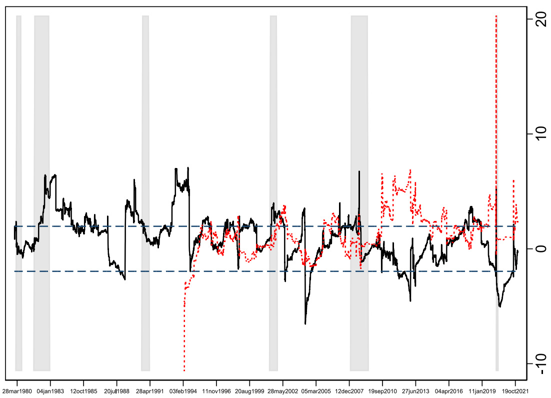
Fig. 6 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signals from T-bill: the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD

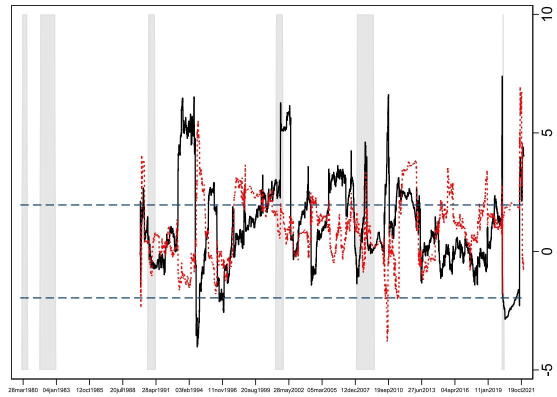


(b) Stock CSAD

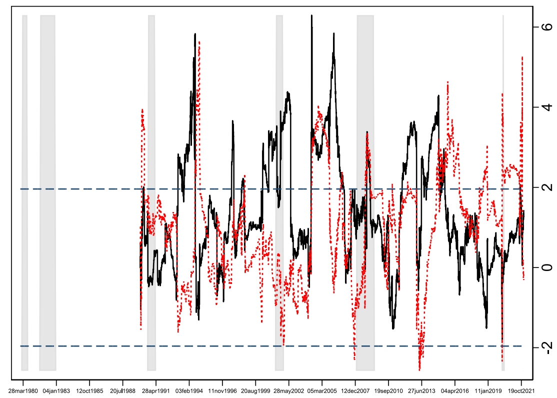


(c) Fix-income CSAD

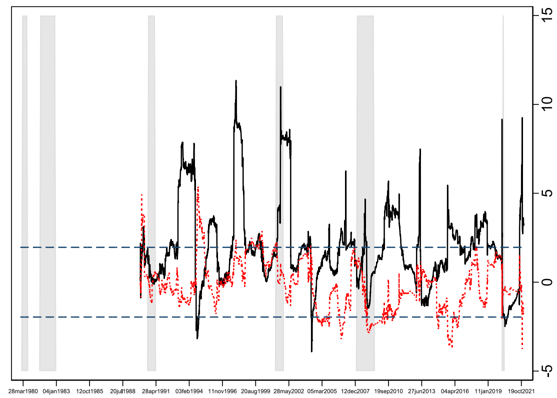
Fig. 7 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signals from CBOE VIX: the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD



(b) Stock CSAD



(c) Fix-income CSAD

ficients are frequently associated with signs opposite to those of γ_2. This pattern indicates that bond-market signals dampen the dispersion dynamics driven by equity-related fundamentals, thereby reducing and contrarian behaviour linked to the stock-like component of REIT pricing.

Panel (c), which reports the rolling window results for the $CSAD_{\text{fixed-income}}$ series, reveals a dampening effect on herding behaviour in the post-GFC period, as evidenced by the opposing signs of γ_2 and γ_{signal} during this interval. These findings suggest that bond-market signals play a stabilising role in the REIT market by moderating dispersion dynamics associated with fixed-income characteristics. More broadly, such signals attenuate both herding and contrarian tendencies at the aggregate market level and across the equity- and fixed-income components of REIT pricing. Similar patterns are observed when signals derived from U.S. government bond yields are incorporated, as documented in Appendix A.5.

Our results so far paint a consistent picture. When the REIT market reacts to changes in stock market performance by shifting probability weights toward extreme values (as per our definition of informational signals), REIT investors prioritise private information linked to stock market fundamentals. This focus amplifies excess return dispersion associated with stock characteristics while reducing dispersion related to fixed-income characteristics. Signals from debt markets exhibit a similar pattern: they intensify contrarian tendencies in the fixed-income CSAD series, and increase herding tendencies in the stock CSAD series.

The CBOE VIX index measures the expected stock market volatility, representing sentiment in the stock market. Our signals based on VIX are derived when the REITs market shifts the probability weight to extreme values during changes in market sentiment. Figure 7 presents a story similar to signals from S&P, with VIX signals predominantly exhibiting an ‘amplifying’ effect on contrarianism in the overall REITs market (Panel (a)). These ‘amplifying’ effects are mainly associated with increased excess return dispersion in stock market fundamentals (Panel (b)), whereas changes in stock market sentiment are linked to reduced dispersion in REITs returns characterised by fixed-income aspects[14].

Turning attention to results of signals derived from REITs ‘representatives’, namely market capitalisation, allocation to real estate assets, and FFO relative to total assets, presented in the last three columns in Table 4. These signals appear to have little effect on herding or contrarianism in the overall CSAD and $CSAD_{fixed-income}$ series. However, the estimates of γ_{signal} are positive and significant in Panel (b), corresponding to the $CSAD_{stock}$ series. This indicates that large REITs exert a stronger influence on equity-related dispersion dynamics, with signals from these REIT ‘representatives’ amplifying contrarian behaviour linked to the stock-like characteristics of REIT pricing.

The rolling-window estimates, presented in Appendix A.5, further corroborate this interpretation, revealing an increased tendency towards contrarian behaviour in response to these REIT-specific signals, particularly during periods of sustained market expansion leading up to the GFC.

Last but not least, the results on the potential impacts of FTS and recession days are presented in the last three columns in Table 4. As outlined in Section 3, FTS is implicitly defined as days when capital reallocates from the stock market to the bond market. γ_{signal} associated with FTS is significantly negative in Panels (a) and (b), indicating that there is a ‘dampening’ effect on contrarianism during FTS periods. Such effect is also present in Panel

[14] Signals from EPU shows similar patterns, we represent the rolling window results in Appendix A.5.

(c), however γ_{signal} is not statistically significant. These findings are in line with expectation, that when investors shift capitals from the stock market (i.e. sell stocks), the tendency to herd increases. Furthermore, consistent with the findings of Philippas et al. (2013), excess return dispersion is intensified during recession periods, reflecting an increased emphasis on private information during times of crisis. Notably, γ_{signal} is statistically negative in the fixed-income specification. Given that the GFC was triggered by a crisis in the real estate debt market, this result aligns with expectations of reduced return dispersion tied to the fixed-income characteristics of REITs during that period.

To summarise, Hypothesis 4 examines whether informational signals from other financial markets and REIT-specific representatives alter the intensity of herding and contrarian behaviour in REIT returns. Our empirical evidence provides strong support for this hypothesis. The results show that informational signals from external financial markets and REIT-specific representatives significantly influence both the intensity and direction of investor behaviour. These findings reinforce the view that herding and contrarian dynamics in REIT markets are contingent on conditions in related financial markets, overall market sentiment, and are inherently time-varying.

6 Conclusion

Among recent empirical studies, there are mixed results in herding/contrarianism behaviours in REITs. Both behaviours can result in mispricing and inefficiency in the asset market. As REITs are evolving, they become more informational and transparent, this study provides further insights into investors' behaviours in the U.S. equity REITs by examining the return dispersions due to inherent characteristics and the role of exogenous information signals.

Using the empirical approach in Chang et al. (2000), our findings show periods of both herding and contrarianism, with contrarianism being the denominating behaviour in the overall REITs market and most REITs sectors. These findings are generally in line with previous studies that use similar methods (Zhou and Anderson 2012; Philippas et al. 2013; Babalos et al. 2015; Essa and Giouvris 2023).

Once return dispersions are decomposed into stock and fixed-income elements, our results show that investors predominately trade against the market consensus based on both stock and fixed-income information. Periods of herding however, are short and infrequent in both stock and fixed-income series. We also find that when the REIT market reacts to signals from the stock markets, REIT investors prioritise private information linked to stock market fundamentals, amplifying return dispersion associated with stock characteristics while reducing dispersion tied to fixed-income features. Similarly, signals from debt markets intensify contrarian tendencies in the fixed-income series and increase herding tendencies in the stock series. These findings highlight the dual nature of REITs, not only that return dispersions are inherently different between their stock and fixed-income characteritics, information spillovers from the stock and debt markets also drive distinct investor behaviours in REITs.

Our findings also reveal that during FTS days, when investors shift capital from the stock market to the bond market, contrarianism in REITs is dampened. Additionally, signals inferred from REITs 'representives' within the REITs market and during recession period show that excess return dispersion in REITs increases, reflecting the heightened emphasis on private information during these times.

By scrutinising inherent characteristics and informational signals, this paper makes a cohesive contribution to the existing literature. The strong evidence of contrarian behaviour may serve as an indicator of the relative transparency of REITs. If the behaviour is triggered by over-confidence and/or excessive risk-taking (Wei et al. 2015), such behaviour can further cause price distortion and increase volatility in REITs. Publicly traded REITs have implications on price determination in direct real estate (Geltner et al. 2003), the dissection of REITs returns in this paper confirms the notion that REITs investors' behaviours are collectively influenced by the performance of both stocks and fixed-income assets. Our results further emphasise the impact of information from other markets and within REITs on herding/contrarianism behaviors, driven by different market fundamentals and under various market conditions.

A Appendix

A.1 CSAD linear model

According to Chang et al. (2000), the non-linear quadratic relation between *CSAD* and $R_{m,t}$ can be proven intuitively as follows. Assuming R_i is the return for asset *i* ($i = 1, \ldots, N$), and R_m is the return of the market portfolio, the expected return of asset *i* can be derived from CAPM using the equation below:

$$E_t(R_i) = \gamma_0 + \beta_i E_t(R_m - \gamma_0) \tag{10}$$

where γ_0 is the return of zero-beta portfolio, β_i is the market risk sensitivity for asset *i*, and β_m is the systematic risk of an equal-weighted market portfolio.

$$\beta_m = \frac{1}{N}\sum_{i=1}^{N}\beta_i \tag{11}$$

The deviation of asset *i* expected return from the market portfolio expected return can be captured in the absolute value of deviation (AVD), using:

$$\begin{aligned} AVD_{i,t} &= |E_t(R_i) - E_t(R_m)| \\ &= |\beta_i E_t(R_m - \gamma_0) - \beta_m E_t(R_m - \gamma_0)| \\ &= |\beta_i - \beta_m||E_t(R_m - \gamma_0)| \end{aligned}$$

The expected cross-sectional absolute deviation (ECSAD) of asset returns is defined as:

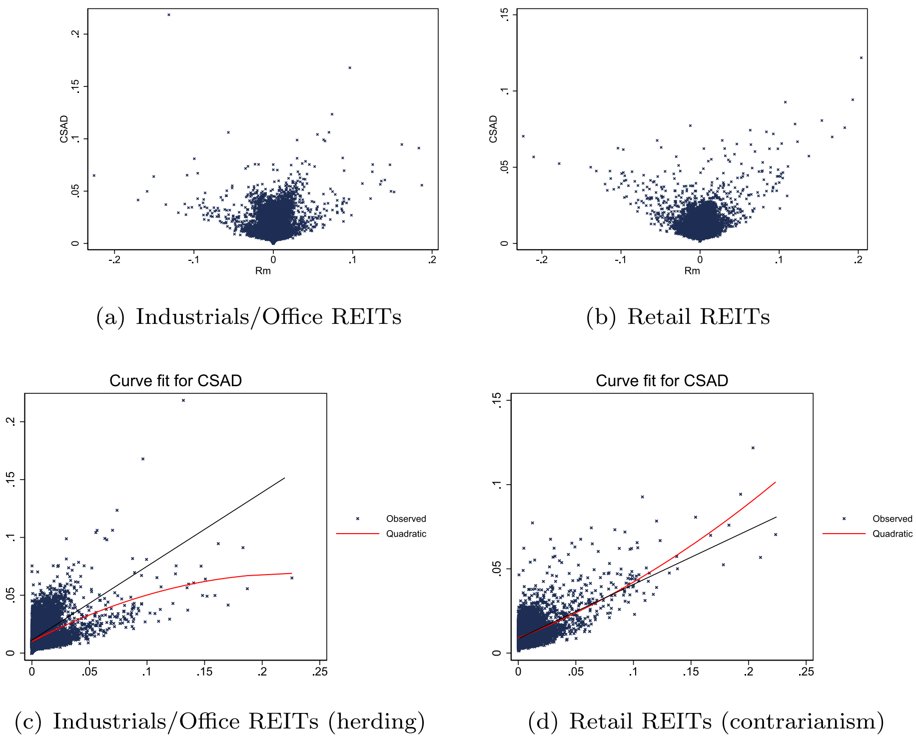
$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N} AVD_{i,t} = \frac{1}{N}\sum_{i=1}^{N} |\beta_i - \beta_m||E_t(R_m - \gamma_0)| \tag{12}$$

The presence of a positive relation between the cross-sectional absolute deviation and return of the market portfolio is shown in:

$$\frac{\partial ECSAD_t}{\partial E_t(|R_m|)} = \frac{1}{N}\sum_{i=1}^{N} |\beta_i - \beta_m| > 0 \tag{13}$$

$$\frac{\partial^2 ECSAD_t}{\partial E_t(|R_m|)^2} = 0 \tag{14}$$

Inspired by Treynor and Mazuy (1966) market timing model, Chang et al. (2000) include an additional quadratic form of R_m in the linear regression of $CSAD_t$ against R_m as an empirical test to capture non-linear adjustment without violating asset pricing model assumptions. In the presence of herding, $CSAD_t$ will increase at a decreasing rate (or decrease) as R_m



(a) Industrials/Office REITs (b) Retail REITs

(c) Industrials/Office REITs (herding) (d) Retail REITs (contrarianism)

Fig. 8 CSAD quadratic fit

increases, which can be reflected as a statistically negative γ_2 in Eq. 2. $\forall\ \gamma_2 < 0$, maximum $CSAD_t = -\gamma_1/2\gamma_2$. The curvature of the herding/contrarian impact on cross-sectional dispersion can be intuitively interpreted as the coefficient of the quadratic term of market return, as the most elegant and simplified measure.

A.2 CSAD dissemination robustness check

As REITs exhibit both characteristics of equity and fixed-income assets, we implement the similar treatment of Lehmann and Modest (1987) and Comer (2006) on market timing model in the CSAD linear regression, where the quadratic terms are extended in multifactor models and the coefficients of each quadratic term reflect herding (or contrarianism) of a specific factor. We use a two-factor Chang et al. (2000) model, in which both stock ($R_{S,t}$) and bond ($R_{B,t}$) factors are considered:

$$CSAD_t = \alpha + \gamma_{1,s}|R_{S,t}| + \gamma_{2,s}R_{S,t}^2 + \gamma_{1,b}|R_{B,t}| + \gamma_{2,b}R_{B,t}^2 + \varepsilon_t \tag{15}$$

The results remain qualitatively indifferent and available upon request.

A.3 Definitions of informational signals

From the general stock and bond markets, we define ‘informational signals’ $D^X_{signal,t} = 1$ when:

$R_{mt} < 0$, but $X_{i,t-2} \geq X_{i,t-1} \leq X_{i,t}$; or $X_{i,t-2} \leq X_{i,t-1} \geq X_{i,t}$. Where X represents the price of the overall stock market or bond market *i*. In this situation, the values of X fluctuate, but the REITs market return is negative. In other words, despite the uncertainty in the stock/bond market, the REITs market shifts towards the probability weight of low value due to some implicit informational signals.

$R_{mt} > 0$, but $X_{i,t-2} \geq X_{i,t-1} \leq X_{i,t}$; or $X_{i,t-2} \leq X_{i,t-1} \geq X_{i,t}$. Similar to the situation above, the values of X fluctuate, but the overall REITs market return is positive, suggesting that the market shifts towards the probability weight of high value.

$R_{mt} < 0$ while $X_{i,t-2} < X_{i,t-1} < X_{i,t}$; and $R_{mt} > 0$ while $X_{i,t-2} > X_{i,t-1} > X_{i,t}$. In these situations, despite that values in X indicate an optimistic (pessimistic) outlook in the stock/bond market, the REITs market does not reflect such information and has negative(positive) returns. This may stem from information asymmetry, leading to a delay in the REITs market reflecting publicly available information. Alternatively, unobserved private information could drive REITs investors to shift the probability weight towards extreme values.

Otherwise $D^X_{signal,t} = 0$.

We apply the same conditions described above to derive signals based on the price changes of REITs ‘representatives’ relative to overall REIT market returns.

Since increases in the CBOE VIX and EPU indices reflect rising volatility and uncertainty, we define $D^{X}_{signal,t} = 1$ when:

$R_{mt} < 0$, but $X_{i,t-2} \geq X_{i,t-1} \leq X_{i,t}$; or $X_{i,t-2} \leq X_{i,t-1} \geq X_{i,t}$, as above.

$R_{mt} > 0$, but $X_{i,t-2} \geq X_{i,t-1} \leq X_{i,t}$; or $X_{i,t-2} \leq X_{i,t-1} \geq X_{i,t}$, as above.

$R_{mt} > 0$ while $X_{i,t-2} < X_{i,t-1} < X_{i,t}$; and $R_{mt} < 0$ while $X_{i,t-2} > X_{i,t-1} > X_{i,t}$. Again, the REITs market return is positive when market volatility or uncertainty increases, and vice versa.

Otherwise $D^{X}_{signal,t} = 0$.

Notably, while our definition of signals shares some similarities with that of Philippas et al. (2020), which also applies a theoretical signal-herding framework, it fundamentally differs in approach. Philippas et al. (2020) directly consider the values of X over time periods $t-1$, $t-2$, and t. For instance, a U-shaped signal is defined when $X_{i,t-2} > X_{i,t-1}$ and $X_{i,t-1} < X_{i,t}$, while a hill-shaped signal is defined as $X_{i,t-2} < X_{i,t-1}$ and $X_{i,t-1} > X_{i,t}$. We argue that these measures primarily capture the volatility in the values of X, rather than providing meaningful insights into private expectations in the REITs market.

A.4 Dynamic herding of different property sectors

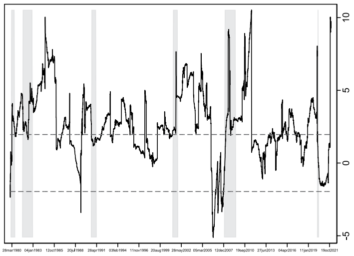
Results from the rolling windows estimation in Figs. 9 and 10 show that on average, localised herding in the Diversified, Healthcare, Industrial/office, Lodging, and 'Others' sectors is associated with the stock characteristics of REITs, whereas contrarianism in all sectors except Industrial/office, is linked with the fixed-income characteristics of REITs. More frequent periods of contrarianism behaviour are observable in all sectors. This pattern persists irrespective of whether return dispersion is measured against stock market fundamentals or fixed-income assets.

A.5 Dynamic herding from signals

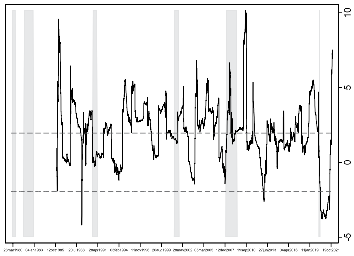
Signals from U.S. government bonds are incorporated, as shown in Fig. 11.

Figure 12 displays increased excess return dispersion across all three panels in response to EPU signals. This suggests that policy-related economic uncertainty may prompt REIT investors to place greater emphasis on their private information, thereby exhibiting a tendency toward reverse herding. Notably, EPU signals have a stronger impact on return dispersion driven by stock fundamentals compared to those influenced by fixed-income characteristics.

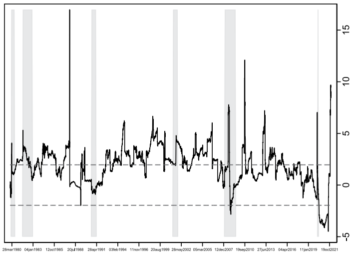
Rolling window estimates of REITs 'representatives', namely marlet cap, real estate allocation, and FFO relative to total assets, are illustrated in Figs. 13, 14, and 15. The results further confirm an increased tendency toward contrarian behaviour, particularly during the market growth period leading up to the GFC.



(a) Diversified

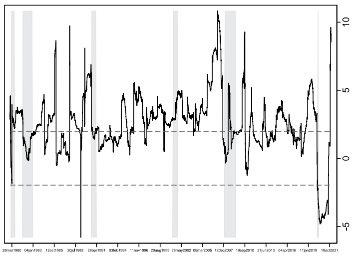


(b) Healthcare

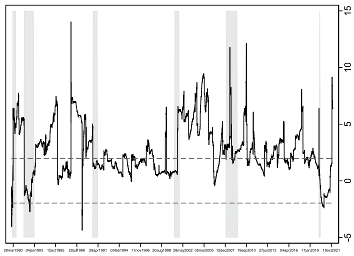


(c) Industrial/Office

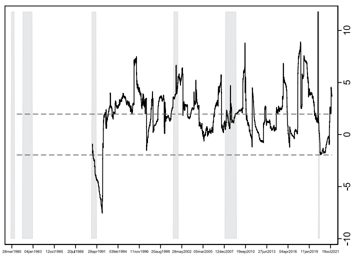
(d) Lodging



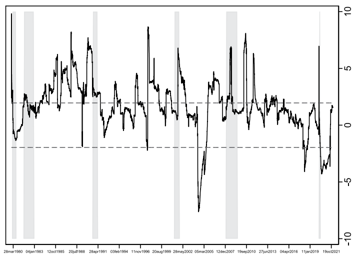
(e) Residential



(f) Retail

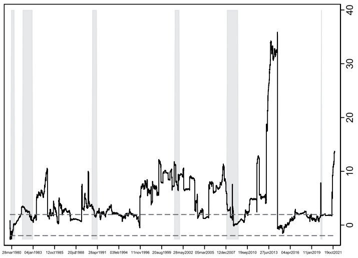


(g) Self-storage

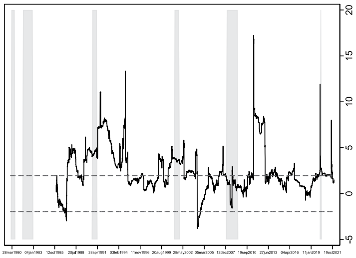


(h) Others

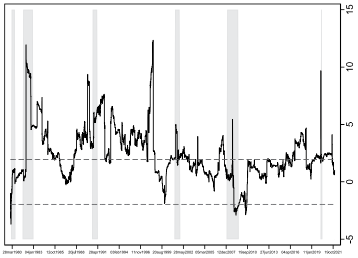
Fig. 9 The t-statistics of γ_2 from the rolling window estimation using $CSAD_{stock}$, by REITs sector: the figure presents the t-statistics of estimated γ_2 in Eq. 2 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



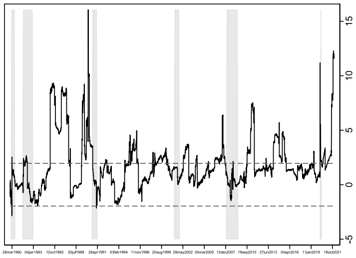
(a) Diversified



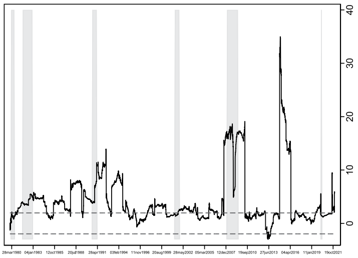
(b) Healthcare



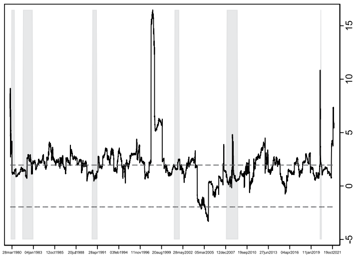
(c) Industrial/Office



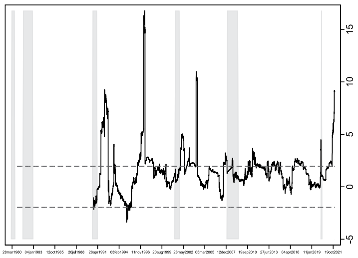
(d) Lodging



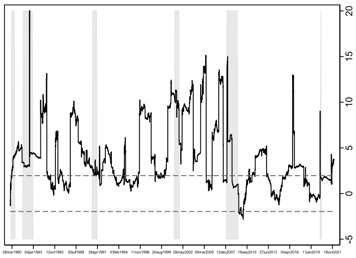
(e) Residential



(f) Retail



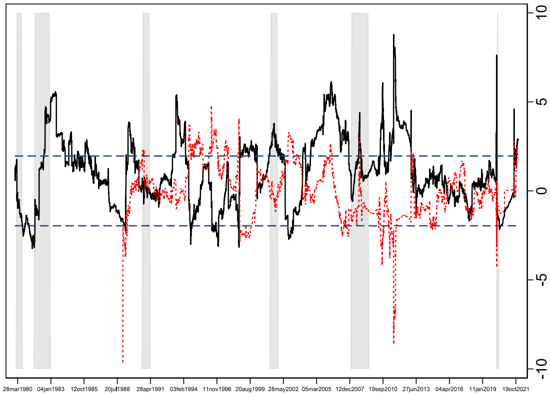
(g) Self-storage



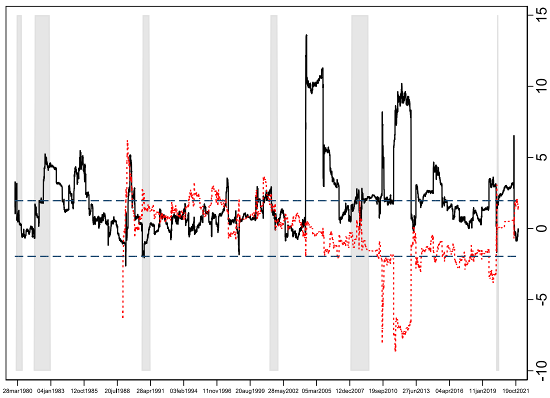
(h) Others

Fig. 10 The t-statistics of γ_2 from the rolling window estimation using $CSAD_{fixed-income}$, by REITs sector: the figure presents the t-statistics of estimated γ_2 in Eq. 2 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows

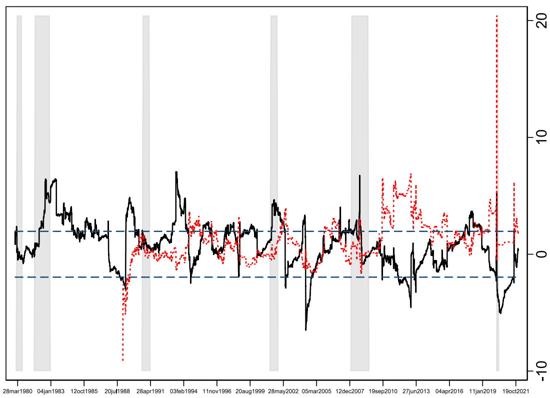
Fig. 11 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signals from US Government bond: the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD

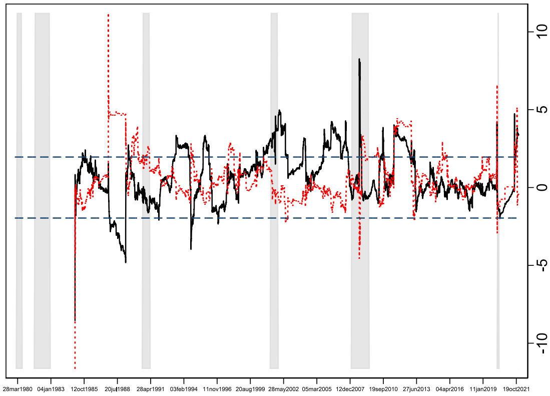


(b) Stock CSAD

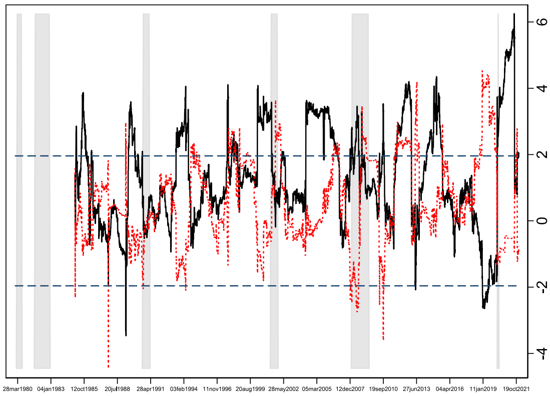


(c) Fix-income CSAD

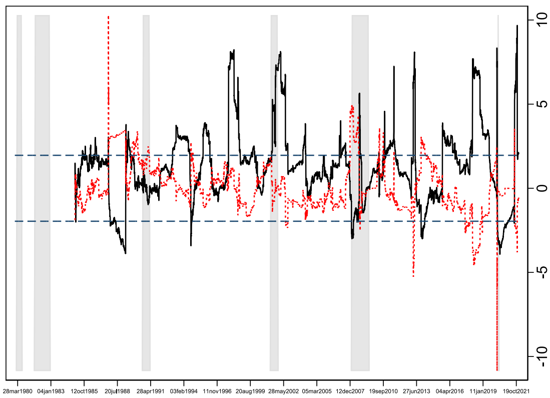
Fig. 12 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signals from EPU: the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD

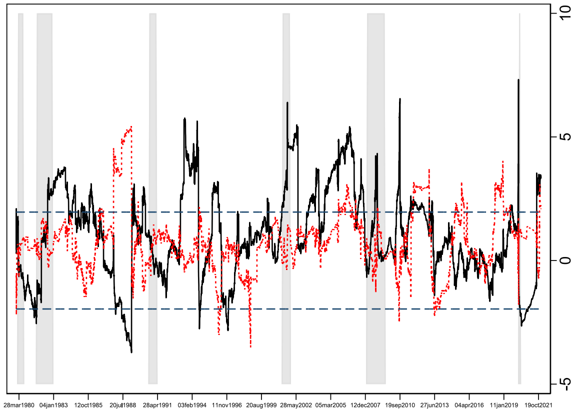


(b) Stock CSAD

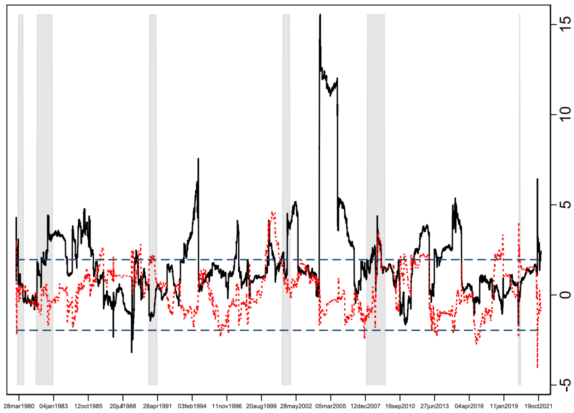


(c) Fix-income CSAD

Fig. 13 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signals from REITs with the largest market caps (top 33%): the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD



(b) Stock CSAD

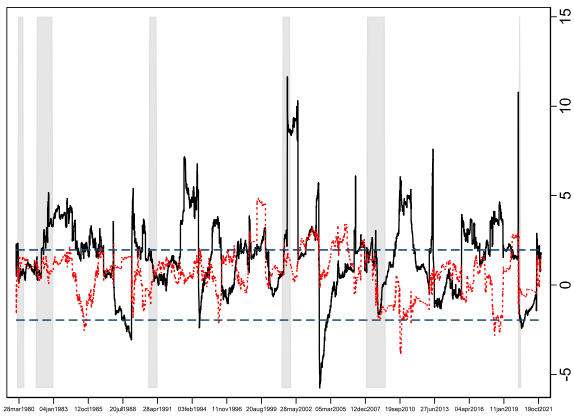
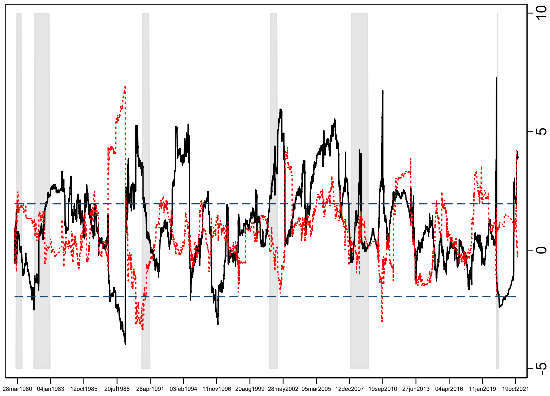
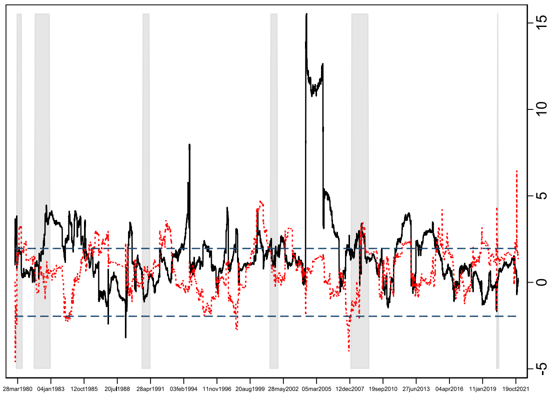


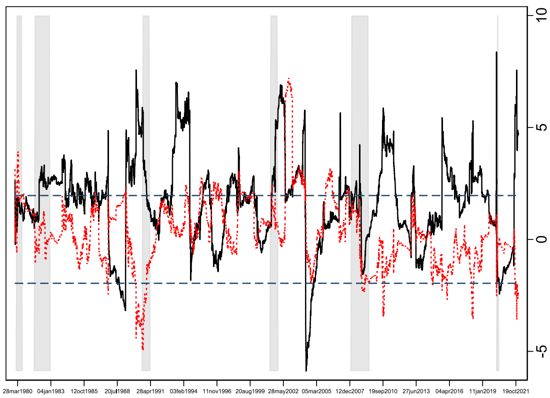
Fig. 14 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signals from REITs with the highest real estate assets allocation (top 33%): the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD

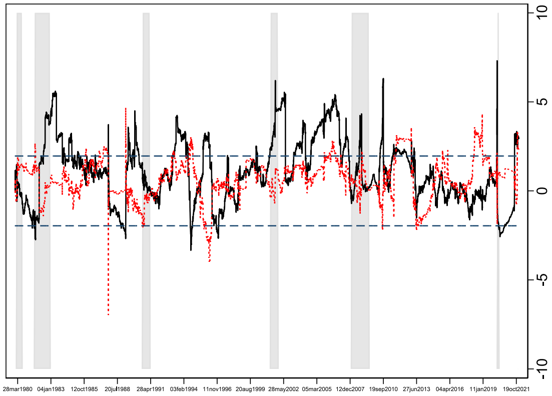


(b) Stock CSAD

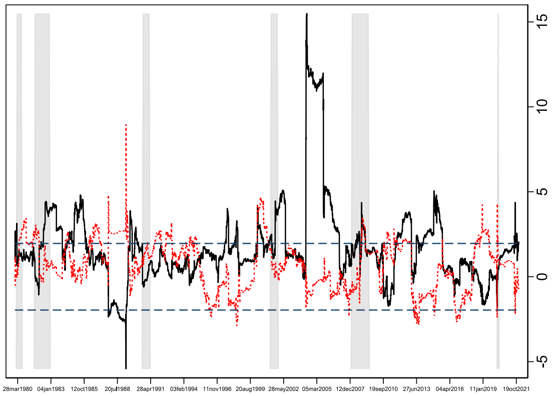


(c) Fix-income CSAD

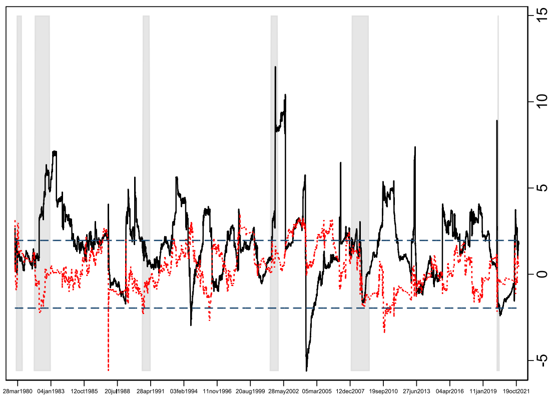
Fig. 15 The t-statistics of γ_2 and γ_{signal} from the rolling window estimation with signal from REITs with the largest FFO on assets (top 33%): the figure presents the t-statistics of estimated γ_2 (solid lines) and those of γ_{signal} (red dotted lines) in Eq. 9 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded areas represent the NBER U.S. Recession indicator periods. Dates on the horizontal axis are the end dates of the rolling windows



(a) All CSAD



(b) Stock CSAD



(c) Fix-income CSAD

A.6 Robustness check using monthly frequency data

We repeated our empirical analysis (Eqs. 1-7) using monthly REITs data. As argued in section 4, the signal analysis does not apply to monthly data analysis. The results are presented in Table 5, 6 and Figs. 16, 17.

A.7 Individual REIT return dissemination by factor models

Following the intuition in Clayton and MacKinnon (2003) that the returns of REITs can be regarded as a hybrid of those of stocks and bonds, we further differentiate a bonds element from REIT returns that are characterised by fixed-income assets. To do so, we decompose individual REIT returns into a linear combination of the products of stock, bond returns and associated sensitivities. The market dispersion subject to stock and bond market can be computed using the product of each market return and market sensitivity ($\hat{\beta}_{s,i}R_{S,t}$ and $\hat{\beta}_{b,i}R_{B,t}$). The remaining unexplained returns including both constant and residual terms are considered as to represent the latent real estate sectors, and are subsequently used to compute CSAD due to the latent real estate factor.

$$R_{i,t} = \alpha + \beta_{s,i}R_{S,t} + \beta_{b,i}R_{B,t} + \varepsilon_t \tag{16}$$

We also replicate our analysis using other asset pricing factor models such as CAPM, Fama French three-factor, Carhart four-factor, and liquidity factor model. The results inferences remain robust and available to readers upon request.

Table 5 Model robustness check using monthly data: Model specifications consist of OLS estimation of Eq. 2 (OLS), linear model with additional autoregressive and heteroskedasticity terms (OLS+AR+GARCH), OLS under rolling window context (the average presented), and other model specifications in Eqs. 3, 4 for the period 1980-2021 for all US Equity REITs

	OLS	OLS+AR+GARCH	Rolling OLS	Yao et al. (2014)	Quantile		
					25%	50%	75%
	Monthly						
γ_1	0.1633***	0.0769***	-0.0204	0.1213***	0.0108	0.1016*	0.2426***
γ_2	0.9563***	0.9436***	4.0123	0.7275***	1.3136***	1.2549***	0.9558***
α	0.0442***	0.0422***	0.0108***	0.0199***	0.0370***	0.0418***	0.0499***
$\gamma_{CSAD,t-1}$		0.7531***		0.5028***			
$ARCH$		0.3535***					
$GARCH$		0.5977***					
Loglikeihood		1587.94					
$Adj-R^2$	45.01%		44.06%	66.37%	9.36%	14.00%	20.34%
T	504	504	504	504	504	504	504

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

The t-statistics are computed using Newey-West HAC robust standard errors

Table 6 Linear regression by sectors using monthly data: The table presents the coefficients and associated t-statistics of Eq. 2, estimated from OLS regression with Newey-West HAC robust standard errors for the period 1980-2021 for different property sectors of US Equity REITs

	Diversified	Healthcare	Industrial/ Office	Lodging	Residential	Retail	Self-storage	Others
	Monthly							
γ_1	0.3689***	0.1947***	0.1397	0.5028***	-0.1074	0.1304***	-0.0556	0.3545***
γ_2	0.3662	0.1815	1.7391	-0.2523	3.0791	0.7700***	0.9674**	1.1852
α	0.0413***	0.0286***	0.0419***	0.0337***	0.0415***	0.0358***	0.0202***	0.0415***
$Adj-R^2$	34.59%	9.32%	43.93%	35.52%	52.74%	52.54%	11.21%	29.91%
T	504	504	504	504	504	504	504	504

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

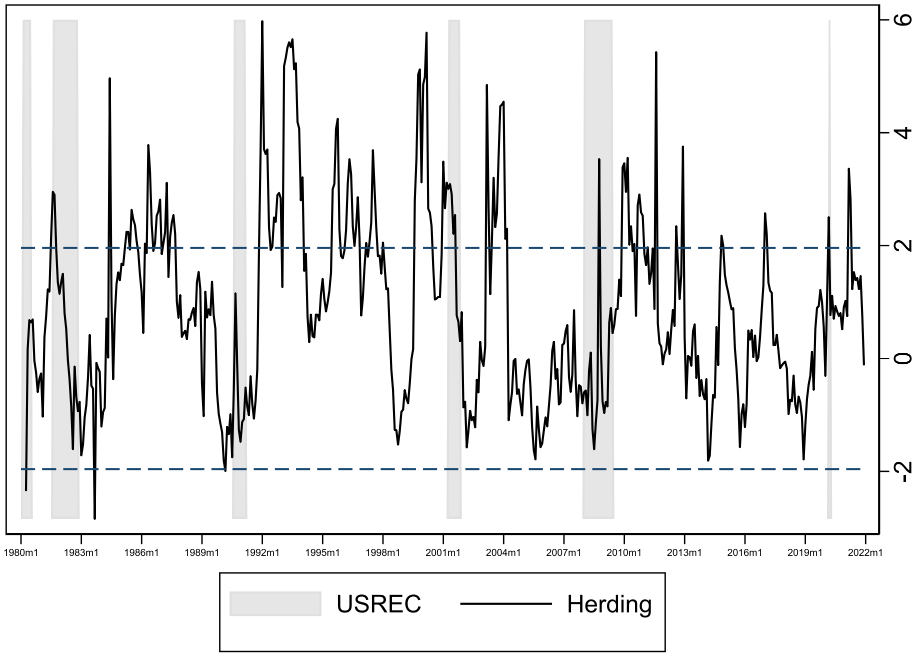
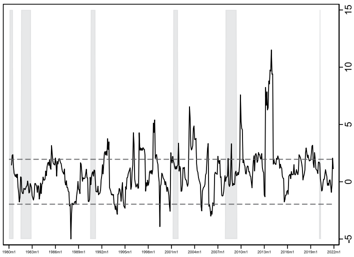
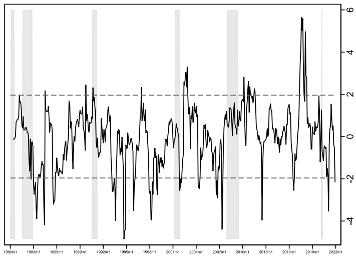


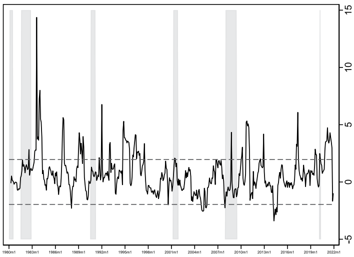
Fig. 16 The t statistics of γ_2 from the rolling window estimation using monthly data: The figure presents the t-statistics of estimated γ_2 in Eq. 2 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded area is the NBER US Recession indicator period. Dates on the horizontal axis are the end dates of the rolling windows



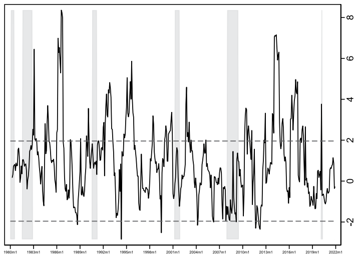
(a) Diversified



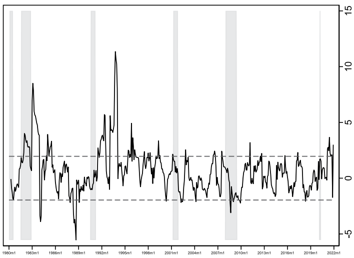
(b) Healthcare



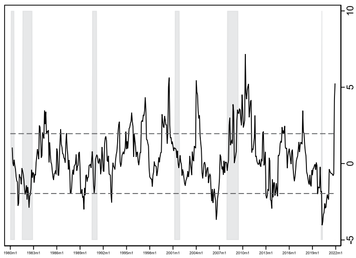
(c) Industrial/Office



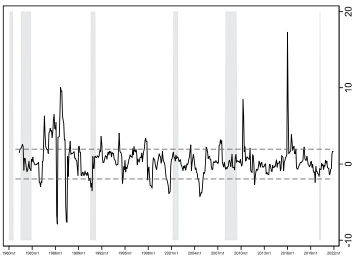
(d) Lodging



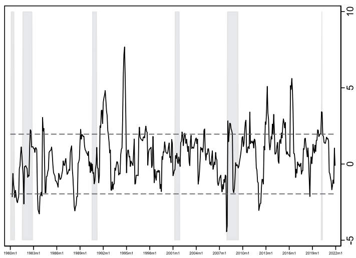
(e) Residential



(f) Retail



(g) Self-storage



(h) Others

Fig. 17 The t statistics of γ_2 from the rolling window estimation using monthly data, by REITs sectors: The figure presents the t-statistics of estimated γ_2 in Eq. 2 with Newey-West HAC robust standard errors, estimated from the lagged one-year rolling window. The shaded area is the NBER US Recession indicator period. Dates on the horizontal axis are the end dates of the rolling windows

Table 7 Linear regression by sectors using daily data: The table presents the coefficients and associated t-statistics of Eq. 2 using *CSAD* from Eq. 15, estimated from OLS regression with Newey-West HAC robust standard errors for the period 1980-2021 for different property sectors of US Equity REITs

	All	Diversified	Healthcare	Industrial/Office	Lodging	Residential	Retail	Self-storage	Others
	OLS of Stock CSAD								
γ_1	0.4856^{***}	0.6527^{***}	0.5878^{***}	0.5663^{***}	0.6692^{***}	0.5761^{***}	0.5120^{***}	0.6564^{***}	0.6545^{***}
γ_2	0.4148	-0.4647^{*}	-0.1158^{*}	0.1395	0.5581^{***}	0.8123	0.7152^{**}	-0.1740	1.3931^{***}
α	0.0025^{***}	0.0023^{***}	0.0032^{***}	0.0027^{***}	0.0025^{***}	0.0024^{***}	0.0029^{***}	0.0026^{***}	0.0019^{***}
$Adj-R^2$	66.42%	70.90%	59.12%	68.81%	78.62%	71.21%	67.23%	64.39%	81.89%
T	10592	10592	10592	10592	10592	10592	10592	10368	10592
	OLS of Bond CSAD								
γ_1	1.001^{***}	0.9942^{***}	0.9957^{***}	1.001^{***}	0.9955^{***}	1.0000^{***}	0.9988^{***}	1.001^{***}	1.004^{***}
γ_2	0.0347	0.0785^{**}	0.0995	0.0262^{*}	0.0162	0.0227	0.0165	0.0696^{***}	-0.0161
α	0.0001^{***}	0.0001^{***}	0.0001	0.0001^{***}	0.0001^{***}	0.0000	0.0001^{***}	0.0000	0.0001^{***}
$Adj-R^2$	99.79%	99.70%	99.11%	99.83%	99.89%	99.84%	99.96%	99.67%	99.51%
T	8316	8316	8316	8316	8316	8316	8316	8316	8316
	OLS of RE CSAD								
γ_1	0.3925^{***}	0.5945^{***}	0.5612^{***}	0.5790^{***}	0.8604^{***}	0.5154^{***}	0.4175^{***}	0.2962^{***}	0.8064^{***}
γ_2	1.3111^{***}	0.3919	-0.5352^{***}	-0.7222^{***}	-0.4590^{*}	2.1106^{***}	0.6805^{**}	0.8429	3.2864^{***}
α	0.0117^{***}	0.0107^{***}	0.0078^{***}	0.0112^{***}	0.0091^{***}	0.0084^{***}	0.0094^{***}	0.0065^{***}	0.0075^{***}
$Adj-R^2$	46.56%	42.85%	40.81%	33.24%	61.51%	52.00%	53.13%	36.80%	73.63%
T	8316	8316	8316	8316	8316	8316	8316	8316	8316

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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