# Health Care REIT Returns & Covid-19: A Note

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*This study tests for pricing efficiency in Healthcare Real Estate Investment Trusts (REITs) surrounding the Covid-19 pandemic. Fractal analysis is used to ascertain whether any persistence or anti-persistence in returns can be observed over the "pre-Covid" and "Covid/post-Covid" periods for the 15 healthcare equity REITs included in the FTSE NAREIT US Real Estate Index. The results point to weak form efficiency during the complete sample period with some exceptions. A relative stability in Hurst exponents exists across the sub-periods for several of the REITs. However, there is evidence that many other REITs series switch from being anti-persistent to persistent, a result consistent with possible herding behavior. Some very limited evidence is found of series switching from being persistent to anti-persistent, consistent with investor overreaction for these REITs. Overall, inefficient pricing is seen in a limited number of cases, but there is a strong suggestion of a possible change like the return dynamic in the latter part of the study period associated with the pandemic.*

*Keywords: market efficiency, persistence, long memory, fractal analysis, REITs, Covid-19*

## INTRODUCTION & BACKGROUND

Recent studies have sought to assess the impact of Covid-19 on different aspects of the REIT market. Akinsomi (2021), for example, discusses the channels through which pandemic-related policies (such as physical distancing and lockdown restrictions) would impact REITs' revenue and cash flow. A flight-to-quality might also be expected, which would impact the performance of the REIT sector in a time of heightened uncertainty. In that study, the returns on global and US REITs for the year ending in May 2020 are shown to be significantly negative, a large reversal from the performance in the previous year. A study by Malhotra & Malhotra (2022) specifically considers Health Care REITs. It suggests that certain accounting statement-based measures of performance, such as Return on Investment, and EBITDA Margin, declined between 2019 and 2020 for a group of 12 healthcare REITs. Rehman et al. (2022) show an increase in returns dependence across small, medium, and large US REITs associated with the COVID-19 event, a feature that has implications for portfolio diversification.

An important recent study, particularly in the context of the present work, is that by Lesame et al. (2024), which documents that the uncertainty attending Covid-19 induced herding behavior among investors in developed market REITs. Fernandez-Martinez et al. (2017) hypothesize that herding behavior can reliably be indicated by the self-affinity index of a time series such as returns which suggests persistence. Along these lines, Aslam et al. (2022) argue that herding behavior can appropriately be modeled using complex systems and they assess possible herding during the pandemic using self-affine or fractal methods of price behavior is six Asian and European stock markets. Mnif et al. (2020) also employ multifractal analysis of returns to assess herding behavior in the cryptocurrency market during the pandemic. Following this approach, the present study estimates the Hurst exponent, or self-affinity index, albeit employing three different methods, viz., the classical rescaled range, roughness length, and wavelets techniques to test for the presence of persistence or anti-persistence in the return series for healthcare REITs.

Even aside from the question of the impact of the recent pandemic on markets, the issue of long memory or persistence in financial series has attracted attention over the last couple of decades (e.g., Diebold & Rudebusch, 1989; Ding et al., 1993; Baillie, 1996; Mulligan, 2000; Cotter & Stevenson, 2008; Hays et al., 2010). The results of several studies that tested for long memory and possible anti-persistence in stock returns questioned the notion that markets are weak-form efficient. Mulligan (2004) reported anti-persistence in returns based on his study of the technology sector in the U.S. Studying the broader market, Hays et al. (2010) found significant persistence in returns for the S&P 500 and NASDAQ indices. Several studies further report risk factors that link REITs and the general stock market (e.g., Chan et al., 1990; Myer & Webb, 1993; Glascock et al., 2000; and Okunev et al., 2000). Taken in conjunction, these two apparent facets of returns behavior, viz. possible persistence in broader market indices and a shared set of risk factors between REITs and the general stock market, suggest the possibility that REIT return series may also be characterized by long memory. Payne & Waters (2007) noted that the REIT sector was a good candidate for the study of pricing behavior. This was both due to their observed integration with the overall stock market and to the fact that these markets lacked liquidity sufficient for the support of more short selling that might normally happen during periods of market overvaluation, for example. This second feature of REITs markets may be expected to attenuate the movement towards equilibrium that might prevent the formation of bubbles.

While the recent pandemic impacted virtually all sectors of the economy, many of them negatively, the present study's focus on healthcare REITs is based on the premise that the health impact of Covid-19 taken together with the policies associated with the pandemic had a particularly large effect (potentially positive *or* negative, *a priori*) on this category of the REIT sector. The next section briefly describes the methods and data employed by the study. A discussion of the results follows this, and the note ends with the overall conclusions that may be drawn from the evidence.

## METHODOLOGY & DATA

This study tests for the presence of long memory or persistence by applying the classical rescaled range methodology, which was proposed by Mandelbrot (1972) to estimate the self-affinity index, or Hurst exponent (H) and fractal dimension. A series is "persistent" (displays long memory) if $H > 0.50$ and "anti-persistent" if $H < 0.50$. Two additional self-affine fractal analysis techniques, viz., roughness length and wavelets, are also used here to estimate H. A detailed description of all three methodologies employed here may be found *among other things* in Mulligan (2004) and Rajagopal & Hays (2012).

To apply classical rescaled-range (R/S) analysis methodology, first a time series **Y** is defined with n consecutive values $\mathbf{Y} = Y_1, Y_2, \ldots, Y_n$. The mean and standard deviation of the series, $Y_m$ and $S_n$, are calculated as usual:

$$Y_m = \frac{\sum_{i=1}^{n} Y_i}{n}; \tag{1}$$

$$S_n = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - Y_m)^2}{n}}. \tag{2}$$

The range, R, is then defined as the difference of the highest and lowest cumulative deviation values of Y over the n observations, that is:

$$R = \mathrm{Max}\left[\sum_{i=1}^{n} (Y_i - Y_m)\right] - \mathrm{Min}\left[\sum_{i=1}^{n} (Y_i - Y_m)\right] \tag{3}$$

Thus, successive deviations from mean are first cumulated through the series of Y values, then minimum and maximum cumulated values are identified, and finally the difference is taken between those two values. As Y has been redefined to a mean of 0, the maximum cumulated deviation will be at least 0, and the minimum at most zero. R will therefore be non-negative. The range can now be viewed as the distance traveled by the series in time n. For systems following Brownian motion, distance covered is proportional to the square root of time, so that for $R = T^{0.5}$ for such systems. A general form of this rule for systems with dependence rather than Brownian motion would be (Hurst, 1951):

$$\frac{R}{S_n} = k \cdot n^H \tag{4}$$

Here, k is a constant, and H is the "Hurst exponent". The left-hand side of the equation above represents the rescaled range, R/S ("range scaled by standard deviation"), and the relationship indicates how the range of cumulated deviations scales over the time increment, n. We would expect the Hurst exponent (H) to be 0.5 for random series. Taking the log of each side, we have:

$$\log\left(\frac{R}{S_n}\right) = \log k + H \cdot \log n \tag{5}$$

Thus, we can estimate H as the slope of the plot of log ($R/S_n$) against log n. To accomplish this in practice the Y series is divided into contiguous sub-periods and H is estimated by OLS (see Peters, 1994, pp. 61-63). For example, we may consider a series consisting of 680 logarithmic returns. The series will be divided successively into periods of length n, with n assuming values of whole integer factors of 680 (i.e. 2, 4, 5, 8, 10, 17, etc.). In the case of each n, an average range and standard deviation will be calculated. For instance, for n of 2, there will 340 windows, for n of 4 there will be 170 windows, etc.). The logarithm of the average R/S value obtained for the window length will be regressed on the logarithm of the window length, n. The coefficient of log n will be the estimated Hurst exponent, or scaling exponent, H. The value of H is 0.50 for a random series, or independent process; if $0.50 < H \leq 1$, the elements in the series influence other elements in the series, and the series is "persistent". The series is "anti-persistent" if $0 \leq H < 0.50$; in this case, the process reverses itself more frequently than a random process would.

The second method used here to estimate the Hurst exponent is that of the Roughness-Length relationship (R/L). This approach is similar to the R/S method, except that the vertical range is replaced with the root-mean-square roughness of the data. Thus, where the average range and standard deviation were calculated in the R/S approach, the root-mean-square roughness is calculated (after adjusting for local linear trend) under the R/L approach. This provides the average root-mean-square roughness for each interval length, which we may denote as *s (w)*. If the trace is self-affine, the roughness measure, *s(w)* is related to the Hurst exponent, *H*, as $s(w) = w^H$. The Hurst exponent is then estimated as in the case of the R/S approach using regression.

Finally, a third method employed to estimate the Hurst exponents is that of Wavelets. This approach uses the fact that the transforms of self-affine traces are themselves self-affine, and involves decomposing the series to be analyzed in time frequency space and assessing variations in power. Fractal properties will be inferred if the wavelet power spectrum is related to frequency by a power law function. As noted by Mulligan (2004), the method is applicable in the case of non-stationary series. The method of Wavelets derives from the work of Beylkin (1992), Coifman et al. (1992), and Daubechies (1990), and its application is briefly described here. T wavelet transforms are taken, each with a distinct scaling coefficient, $K_i$. The standard deviations from 0 of those scaling coefficients are denoted as $S_i$ and $R_i$ represent the T-1 ratios of the standard deviations. Thus, $R_1 = S_1/S_2$, $R_2 = S_2/S_3$, etc. Now, the average of the $R_i$ is estimated as:

$$R_{AVG} = \frac{\sum_{i=1}^{T-1} R_i}{T-1} \tag{6}$$

Finally, the Hurst exponent is estimated as H = Φ ($R_{AVG}$); Φ is a heuristic function approximating H by $R_{AVG}$ for stochastic self-affine series. The present estimation process varies T up to a value of 4, and i takes the values of 0, 1, 2, and 3 for the scaling coefficients. As such, H is estimated using the first three dominant wavelet functions, a process also followed in Mulligan (2004). The wavelet method does not yield a standard error for hypothesis testing.

The sample consists of the 15 healthcare equity REITs which are included in the FTSE NAREIT US Real Estate Index. All available price data for each of these REITs are used to estimate the Hurst exponent for the corresponding return series spanning the "full" sample period ending on October 9, 2023. The analysis is then repeated for two sub-periods: the "pre-pandemic" period ending on December 31, 2019, and the "pandemic/post-pandemic" period starting on January 1, 2020. Naturally, the latter period is considerably shorter for most of the healthcare REITs in the sample. The two exceptions are Global Medical REIT (GMRE-PA), which has 577 and 949 observations in the "pre-pandemic" and "pandemic/post-pandemic" periods, respectively, and Strawberry Fields REIT (STRW), for which only 144 observations are available, all in the "pandemic/post-pandemic" period. Table 1 below lists the Health Care REITs included in the study.

**TABLE 1**
**SAMPLE OF HEALTH CARE REITs**

| **Real Estate Investment Trust** | **Symbol** | **Data Start Date** | **No. of Observations** | | |
|---|---|---|---|---|---|
| | | | *Full* | *Pre-Covid* | *Post* |
| Care Trust REIT, Inc. | CTRE | 05.29.2014 | 2358 | 1409 | 949 |
| Diversified Healthcare Trust | DHC | 02.23.2000 | 5945 | 4996 | 949 |
| Physicians Realty Trust | DOC | 07.19.2013 | 2574 | 2480 | 949 |
| Global Medical REIT, Inc. | GMRE | 09.14.2017 | 1527 | 578 | 949 |
| Healthcare Realty Trust Inc. | HR | 05.27.1993 | 7647 | 6698 | 949 |
| LTC Properties, Inc. | LTC | 08.18.1992 | 7843 | 6894 | 949 |
| Medical Properties Trust, Inc. | MPW | 07.08.2005 | 4595 | 3646 | 949 |
| National Health Investors, Inc. | NHI | 10.09.1991 | 8060 | 7111 | 949 |
| Omega Health Care Investors, Inc. | OHI | 08.07.1992 | 7850 | 6901 | 949 |
| Healthpeak Properties, Inc. | PEAK | 05.23.1985 | 9672 | 8723 | 949 |
| Sabra Healthcare REIT, Inc. | SBRA | 04.02.2002 | 5419 | 4470 | 949 |
| Strawberry Fields REIT, Inc. | STRW | 02.22.2023 | 159 | 0 | 159 |
| Universal Health Realty Income Trust | UHT | 12.26.1986 | 9270 | 8321 | 949 |
| Ventas, Inc. | VTR | 05.05.1997 | 6652 | 5703 | 949 |
| Welltower, Inc. | WELL | 03.19.1980 | 10982 | 10033 | 949 |

The following section reports and discusses the results of the classical rescaled range, roughness length, and wavelets analyses for the full sample period and the two subperiods relative to the pandemic. As data were insufficient for estimation purposes in the case of STRW, results are not reported for that REIT.

## RESULTS & DISCUSSION

Table 2 below presents the results for the complete or "full", the "pre-Covid", and the "Covid/post-Covid" samples obtained from the three fractal analytical techniques discussed above. The estimated Hurst exponents (H) and the number of window intervals (*w*) are reported for the rescaled range and roughness length analyses. Rejection of the null hypothesis of H = 0.500 is indicated at significance levels of 1%, 5%, and 10% where applicable. For the wavelets analysis, the estimated Hurst exponents are reported along with the number of observations in the trace; the estimation process does not yield standard errors for hypothesis testing.

The roughness length methodology leads to a rejection of the null very frequently, and this is often due to a consistently low standard error reported for the estimated H. Consequently, as a conservative rule of thumb, the present study does not rely exclusively on the conclusions derived from the roughness length method but instead looks for a consensus across the three methods.

For the total sample, the rescaled range analysis suggests a predominance of weak-form efficiency across the REITs. There are two notable exceptions, however. Global Medical REIT (GMRE) returns are shown to be significantly anti-persistent, with an estimated H of 0.447. This is further confirmed by the roughness length and wavelets methods, which respectively indicate H exponents of 0.391 and 0.369. Confirmation of anti-persistence with wavelets is noteworthy as GMRE is the only REIT in the sample for which the wavelets method estimates an exponent lower than 0.500 for the entire sample period. Such anti-persistence indicates that this equity is more volatile than would be suggested by a random walk and is consistent with the notion that the market tends to overreact to information in the case of GMRE.

A second notable exception in the rescaled range results of efficient pricing for the entire sample period is Sabra Health Care REIT (SBRA). In the case of this REIT, however, a strong persistence or long memory is indicated, with an H of 0.559. This result is further confirmed by the roughness length and wavelets methods, which estimate the Hurst exponent to be 0.547 and 0.575. Thus, there are indications that SBRA has a trend-reinforcing return series, and that this equity presents an opportunity for excess profits to be extracted through technical trading rules. In the case of SBRA, confirmation of persistence with roughness length is particularly noteworthy as it is the only REIT in the sample for which this method estimates a Hurst exponent greater than 0.500 in the full sample period.

The results in Table 2 further reveal that within each of the three methods, there is a fair degree of stability in the estimated H across the "full" and "pre-Covid" periods. However, based on roughness length estimates of H, there is a switch between persistence and anti-persistence in the case of several REITs as the study moves from the "pre-Covid" subperiod to the "Covid/post-Covid" subperiod. It is interesting to note that half of the sample's series switch from being anti-persistent to persistent: CTRE, DHC, LTC, NHI, UHT, VTR, and WELL. While caution is needed in interpreting this result due to the reduction in the length of the sample period, the switch is certainly suggestive especially in light of some recent studies, such as Lesame et al. (2024) mentioned earlier which documents that the uncertainty associated with Covid-19 induced herding behavior among investors in REITs. As argued by Fernandez-Martinez et al. (2017), herding behavior may reliably be captured by the self-affinity measure that reveals persistence in a series. It is also apparent that the wavelets estimates of the Hurst exponent consistently increase further beyond 0.500 for as many as 10 of the 14 healthcare REITs as the analysis shifts from the pre-Covid subperiod to the Covid/post-Covid subperiod.

Based on rescaled range analysis, there are 4 series that were not anti-persistent in the pre-Covid subperiod but switched to being anti-persistent in Covid/post-Covid subperiod: DOC, HR, LTC, and OHI. Anti-persistence in three of these series for the latter period is also confirmed by roughness length (LTC being the exception, which, as mentioned above, is shown by the roughness length method to be persistent in the Covid/post-Covid period). Furthermore, the result of anti-persistence in the latter period for OHI is not supported by the evidence supplied by wavelet analysis, which suggests an increase in the estimated H from 0.554 to 0.634 for this REIT. There is therefore some indication of a switch from persistence to anti-persistence during and after the pandemic in a couple of healthcare REITs (DOC & HR), which would indicate a tendency for investor overreaction to new information in those cases.

**TABLE 2**
**HURT EXPONENTS FOR HEALTHCARE REITs**

| REITs | | Classical Rescaled Range | | | Roughness Length | | | Wavelets | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **Full** | **Pre-Covid** | **Post-Covid** | **Full** | **Pre-Covid** | **Post-Covid** | **Full** | **Pre-Covid** | **Post-Covid** |
| CTRE | **H** | 0.522$^{*}$ | 0.495 | 0.509 | 0.478$^{***}$ | 0.473$^{*}$ | 0.542$^{***}$ | 0.608 | 0.609 | 0.614 |
| | ***w*** | 30 | 26 | 22 | 24 | 20 | 16 | 2048 | 1024 | 512 |
| DHC | **H** | 0.479 | 0.457 | 0.484 | 0.454$^{***}$ | 0.451$^{***}$ | 0.506$^{*}$ | 0.614 | 0.512 | 0.753 |
| | ***w*** | 39 | 38 | 22 | 42 | 32 | 16 | 4096 | 4096 | 512 |
| DOC | **H** | 0.465 | 0.459 | 0.413$^{**}$ | 0.427$^{***}$ | 0.420$^{***}$ | 0.457$^{***}$ | 0.531 | 0.556 | 0.602 |
| | ***w*** | 37 | 26 | 22 | 30 | 20 | 16 | 2048 | 1024 | 512 |
| GMRE | **H** | 0.477$^{***}$ | 0.403$^{***}$ | 0.387$^{***}$ | 0.391$^{***}$ | 0.243$^{***}$ | 0.403$^{***}$ | 0.369 | 0.364 | 0.452 |
| | ***w*** | 26 | 15 | 22 | 20 | 10 | 16 | 1024 | 512 | 512 |
| HR | **H** | 0.477 | 0.476 | 0.398$^{***}$ | 0.444$^{***}$ | 0.434$^{***}$ | 0.466$^{***}$ | 0.502 | 0.509 | 0.583 |
| | ***w*** | 53 | 44 | 22 | 46 | 42 | 16 | 4096 | 4096 | 512 |
| LTC | **H** | 0.492 | 0.490 | 0.469$^{***}$ | 0.450$^{***}$ | 0.437$^{***}$ | 0.515$^{***}$ | 0.542 | 0.533 | 0.534 |
| | ***w*** | 53 | 46 | 22 | 46 | 41 | 16 | 4096 | 4096 | 512 |
| MPW | **H** | 0.506 | 0.507 | 0.455 | 0.467$^{***}$ | 0.467$^{***}$ | 0.452$^{***}$ | 0.565 | 0.550 | 0.690 |
| | ***w*** | 38 | 38 | 22 | 32 | 32 | 16 | 4096 | 2048 | 512 |
| NHI | **H** | 0.506 | 0.508 | 0.477 | 0.437$^{**}$ | 0.442$^{***}$ | 0.517$^{***}$ | 0.557 | 0.515 | 0.620 |
| | ***w*** | 53 | 46 | 22 | 46 | 42 | 16 | 4096 | 4096 | 512 |
| OHI | **H** | 0.521 | 0.522 | 0.452$^{***}$ | 0.496 | 0.503 | 0.493$^{***}$ | 0.531 | 0.554 | 0.634 |
| | ***w*** | 53 | 46 | 22 | 46 | 41 | 16 | 4096 | 4096 | 512 |
| PEAK | **H** | 0.474 | 0.482 | 0.457 | 0.439$^{***}$ | 0.442$^{***}$ | 0.498 | 0.519 | 0.534 | 0.534 |
| | ***w*** | 54 | 50 | 22 | 48 | 46 | 16 | 8192 | 8192 | 512 |
| SBRA | **H** | 0.559$^{***}$ | 0.544$^{***}$ | 0.495 | 0.547 | 0.528 | 0.503 | 0.575 | 0.585 | 0.585 |
| | ***w*** | 49 | 38 | 22 | 42 | 32 | 16 | 4096 | 4096 | 512 |
| UHT | **H** | 0.456 | 0.447 | 0.450 | 0.430$^{***}$ | 0.424$^{***}$ | 0.540$^{***}$ | 0.503 | 0.480 | 0.611 |
| | ***w*** | 54 | 53 | 22 | 48 | 46 | 16 | 8192 | 8192 | 512 |
| VTR | **H** | 0.514 | 0.508 | 0.509 | 0.488$^{*}$ | 0.488$^{*}$ | 0.543$^{***}$ | 0.520 | 0.526 | 0.620 |
| | ***w*** | 44 | 38 | 22 | 42 | 42 | 16 | 4096 | 4096 | 512 |
| WELL | **H** | 0.497 | 0.499 | 0.478 | 0.463$^{***}$ | 0.458$^{***}$ | 0.523$^{***}$ | 0.528 | 0.523 | 0.581 |
| | ***w*** | 61 | 54 | 22 | 54 | 48 | 16 | 8192 | 8192 | 512 |

$^{***}$Significant at the 1% level
$^{**}$Significant at the 5% level
$^{*}$Significant at the 10% level

## CONCLUSION

This study conducted a fractal analysis of the pricing of Healthcare REITs to evaluate whether the return series displayed any persistence (long memory) or anti-persistence. An important objective was to compare the self-affinity or Hurst index across two periods, one predating the pandemic and the other covering the pandemic and after. The notion of weak-form efficiency could not be rejected for the full sample period, except in the case of GMRE (anti-persistent) and SBRA (persistent). Comparing the sub-periods, however, many of the series appeared to switch from being anti-persistent to persistent. This result suggests a herding behavior among investors in a sector that may have been subject to unusual uncertainty on account of the pandemic and associated policies. Additionally, limited evidence was found of some REIT series switching from persistence to anti-persistence across the two subperiods, a result that would be consistent with investor overreaction to information. Thus, there are some indications of inefficient pricing in a limited number of cases for the full sample period, and the suggestion of a possible change in return dynamics in the latter part of the study period spanning the pandemic and after, consistent with herding behavior among investors at least in this segment of the REITs market.

The findings in this study are consistent with those reported by Lesame et al. (2024), which indicate that the uncertainty stemming from the recent health crisis induced herding behavior among investors in developed market REITs. While their study considers broader REITs indices from 27 countries, the present study focuses on individual REITs specifically included in the major US health care REITs index. Results here also agree with the Aslam et al. (2022) study that using high-frequency (15-minuted interval) data for equity indices between January and December 2020, report herding behavior in Asia and Europe due to the Covid-19 event. As these preceding studies note, evidence of pricing inefficiencies and tendencies towards herding during an event such as an international health crisis should be of interest to individual investors and portfolio managers alike as they could potentially provide profitable trading rules and impact the diversification benefits from investing in this asset class. Furthermore, possible destabilizing volatility effects due to herding behavior should concern policy makers.

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