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A high-frequency analysis of the interactions between REIT return and volatility

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ABSTRACT

This paper makes the first attempt in the real estate literature to test the two hypotheses depicting the interactions between return and volatility — the leverage effect and volatility feedback effect. By employing high-frequency data, we find that both leverage and volatility feedback effects are at work and highly persistent in the U.S. REIT market. The leverage effect dominates the volatility feedback effect. More importantly, both effects are found nonlinear — a feature matching the tendency of the financial market to often change its behavior. Further analysis suggests that the nonlinearity arises from multiple sources (e.g. regime switching, structural breaks, and outliers). Our findings are robust to different data sampling frequencies. All in all, they lead to a better understanding of the recent movement of REIT volatility and have profound implications for asset pricing.

1. Introduction

It is a well-documented finding in finance that equity returns and volatility are negatively correlated. That is, volatility tends to rise following negative returns and falls following positive ones. This phenomenon is often referred to as asymmetric volatility in the literature (for the general equity market, see e.g. Engle and Ng, 1993; Zakoian, 1994; for the real estate sector, see, e.g. Hung and Glascock, 2010; Jirasakuldech et al., 2009; Yang et al., 2012; Zhou and Nicholson, 2015). The asymmetry between return and volatility plays an essential role in volatility modeling. A variety of econometric models have been developed to capture the feature (e.g. the Exponential GARCH of Nelson, 1991, the asymmetric GARCH of Glosten et al., 1993). It is also found to have important implications for equity pricing and portfolio diversifications (Wu, 2001; Thorp and Milunovich, 2007; Zhou and Nicholson, 2015).

A fully consistent economic theory has not yet been developed to explain the phenomenon. Two hypotheses have been proposed instead: one is the leverage effect hypothesis (e.g. Black, 1976; Christie, 1982), which states that a drop of stock price (negative return) increases financial leverage, which makes stock riskier, and as a result its volatility rises; the other is volatility feedback hypothesis, which is related to time-varying risk premium (e.g. Pindyck, 1984; French et al., 1987; Campbell and Hentschel, 1992): if volatility is priced, an anticipated increase in volatility raises the required rate of return, leading to an immediate stock price decline (negative return). The two hypotheses have been extensively examined for the stock market and the results are quite mixed. For instance, early studies of Christie (1982) and Schwert (1989) lend support to the leverage effect while others (e.g. French et al., 1987, Campbell and Hentschel, 1992) find evidence for the volatility feedback effect. More recent studies tend to use a framework to incorporate both effects and compare their relative importance. The results are still ambiguous: studies of Bollerslev et al. (2006), Masset and Wallmeier (2010), and Dufour et al. (2012) find that the leverage effect prevails over the feedback effect, whereas Bekaert and Wu (2000) and Dennis et al. (2006) have opposite findings.

In this paper, we try to test the two hypotheses for the securitized real estate market. There are several reasons why we focus on this market. First, securitized real estate (namely, real estate securities) constitutes an attractive alternative to the mainstream investment vehicles (stocks and bonds) by allowing easy access to real estate investments without directly owning or managing the underlying assets. In essence, they are securities issued based on a pool of income-producing properties and/or mortgages, and can be traded in financial exchanges. Second, the sector has become increasingly important. Its global market capitalization, according to Standard & Poor Global REIT Index, has grown at an average rate of 12.33% per annum over the last 15 years, reaching around US$572 billion in 2011. Third, in addition to its distinctive characteristics as an asset class, securitized real estate is more strictly regulated than regular stock-issuing corporations. One of the regulatory rules requires REITs — the dominant form of securitized real estate to pay out a high portion of net income as dividends to shareholders each year. As will be shown later, this unique feature has important implications for our findings. Finally, no one has yet rigorously examined the two hypotheses for the sector. We find that previous researchers simply choose to use the hypothesis best suited to explaining their findings, without testing first which one(s) is actually at work. For example, Hung and Glascock (2010) offered a description of the two theories and then chose to use the volatility feedback theory to analyze momentum

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returns for U.S. REITs. Another study of Yang et al. (2012) also mentioned the importance of the two alternative theories but opted to use the leverage effect theory to explain asymmetry volatility for U.S. REITs.

Given the above discussions, we aim to extend the literature along several lines. First, we will try to see what effect or perhaps both exist in the securitized real estate market. This would enhance our understanding of the risk–return dynamics in this expanding sector. Second, in addition to examining linear effects, we consider nonlinear effects. In so doing we aim to overcome a major shortfall of the current literature which predominantly examine the two hypotheses in a linear specification. We conjecture that the two effects might take place in a nonlinear fashion. Such an angle could help reveal new evidence. Third, on observing the central difference of the two hypotheses lies in the direction of the causality (the leverage effect is return-driven while the volatility feedback effect is volatility-driven), if they were found to coexist, we would compare their relative importance by measuring the strength of causality. Measuring causality strength is a subject worth pursuing in itself. As a matter of fact, most of the literature is focused on checking the presence of causality, leaving much less attention to how to quantify causality (Song and Taamouti, 2013). Fourth, we will carry out the investigations using high frequency data. This type of data has been increasingly used in the stock market to study the interactions between return and volatility (e.g. Bollerslev et al., 2006, Masset and Wallmeier, 2010, Dufour et al., 2012). The reason, as noted by Dufour et al. (2012), is that a major complication in detecting causality is temporal aggregation and using high frequency data increases the chance to detect causal links, which may otherwise elude the examination using low frequency data. To our best knowledge, this study is also the first one to employ high frequency data to study REIT return and volatility.

In using high-frequency data, however, a well-known issue is that they are subject to market microstructures (bid-ask bounces, discrete price observations, irregular trading, etc.) which cause bias in the intraday measures of volatility. To deal with the issue, we follow a common practice to use data of the 5-min frequency. Interval of this size is believed to be long enough for the adverse effects of market microstructure not to be excessive, and short enough for the daily volatility dynamics to be picked up with reasonable accuracy (e.g. Andersen et al., 2003; Bollerslev et al., 2006). Our data source is FTSE EPRA/NAREIT price index from Bloomberg. Our data sample is from Jan 2008 to Dec 2014. Using the raw 5-min data as building blocks, we carry out the investigation at four levels of sampling frequency: 15 min, 30 min, 1 h, and daily. Our findings suggest that both leverage and volatility feedback effects are at work and highly persistent. More importantly, both are found nonlinear. Further analyses show that multiple sources (e.g. regime switching, structural breaks, outliners) contribute to the presence of nonlinearity. In addition, we find that the leverage effect dominates the volatility feedback effect. The above findings are robust to the sampling frequencies. Our findings lead to a better understanding of the recent movement of REIT volatility, in particular, the bout of uncharacteristically high volatility during the recent financial crisis. Furthermore, our results underscore the importance of considering nonlinearity in the REIT return-volatility relationship, which is expected to have significant impacts on asset pricing.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 discusses the methodologies. Section 4 describes the data; Section 5 presents the empirical findings and discusses their financial implications; and the last section concludes.

2. Econometric methodologies

The fundamental difference between the two hypotheses lies in the direction of interactions. The leverage effect is return-driven as it explains why a negative (positive) return causes a higher (lower) subsequent volatility, whereas the volatility feedback effect is volatility-driven as it justifies how an anticipated increase (decrease) in volatility causes a negative (positive) return. So a natural method for testing the two hypotheses is Granger causality (e.g. Masset and Wallmeier, 2010, Dufour et al., 2012). In what follows we briefly discuss the econometric methodologies.

2.1. Linear Granger causality

Consider two time series X_t and Y_t. Linear Granger causality investigates whether past values of X_t have linear predictive power for the current value of Y_t. If so, X_t is said to linearly Granger cause Y_t. Bidirectional causality exists if causality runs in both directions. Testing for linear causality can be easily implemented within a vector autoregression (VAR) framework:

$$r_t = \alpha_1 + \sum_{i=1}^{T_{11}} \beta_{11,i} r_{t-i} + \sum_{j=1}^{T_{12}} \beta_{12,j} \sigma^2_{t-j} + \varepsilon_{1,t} \tag{1}$$

$$\sigma^2_t = \alpha_2 + \sum_{j=1}^{T_{21}} \beta_{21,j} r_{t-j} + \sum_{i=1}^{T_{22}} \beta_{22,i} \sigma^2_{t-i} + \varepsilon_{2,t} \tag{2}$$

where r_t and σ^2_t are, respectively, return and volatility at time t. α and β are the parameters to be estimated. ε_1 and ε_2 are error terms. Lag lengths (T_{ij}) are determined by information criteria like the Bayesian information criterion (BIC). Given the VAR of Eqs. (1)–(2), testing for Granger causality is equivalent to testing $\sum \beta_{12,j} = 0$ (for $\sigma^2 \to r$) or $\sum \beta_{21,j} = 0$ (for $r \to \sigma^2$). This can be done using a simple F-test.

To assess linear causality strength, we follow the procedure of Geweke (1982). First define a restricted VAR by setting $\beta_{12,j} = 0$ and $\beta_{21,j} = 0$. Let $\hat{\hat{\varepsilon}}_1$ and $\hat{\hat{\varepsilon}}_2$ denote the error terms estimated from this restricted model. Then we obtain the causality measures as follows:

$$C_{r\to\sigma^2} = \ln\left(Var\left(\hat{\hat{\varepsilon}}_2\right) / Var(\hat{\varepsilon}_2)\right) \tag{3}$$

$$C_{\sigma^2\to r} = \ln\left(Var\left(\hat{\hat{\varepsilon}}_1\right) / Var(\hat{\varepsilon}_1)\right) \tag{4}$$

where $C_{X\to Y}$ represents the causality strength from X to Y, $\hat{\varepsilon}_1$ and $\hat{\varepsilon}_2$ are the error terms estimated from the unrestricted VAR of Eqs. (1)–(2), $Var(\cdot)$ is the variance of the variable of interest. To see why Eqs. (3)–(4) constitute measures of causality, notice that if r does not linearly Granger cause (i.e. has no predictive power for) σ^2, then $Var(\hat{\varepsilon}_2)$ would equal $Var(\hat{\hat{\varepsilon}}_2)$, in which case $C_{r\to\sigma^2} = 0$. Conversely when r indeed linearly Granger causes σ^2, the more r helps predict σ^2, the more $Var(\hat{\varepsilon}_2)$ would fall below $Var(\hat{\hat{\varepsilon}}_2)$ and the larger $C_{r\to\sigma^2}$. $C_{\sigma^2\to r}$ can be interpreted similarly.

2.2. Nonlinear Granger causality

2.2.1. Diagnostic testing of nonlinear causality

Eqs. (1)–(2)) are apparently a linear system. To detect nonlinear causality, we turn to the procedure of Baek and Brock (1992), which represents an important development in nonlinear causality testing. The strength of the procedure lies in its nonparametric nature: it does not make any assumption for the functional form of nonlinearity, which arguably can take place in a variety of fashions. This procedure was later augmented by Hiemstra and Jones (1994) and Diks and Panchenko (2006). Below we briefly discuss the procedure, based on Diks and Panchenko (2006).

In a nonparametric setting, testing the null hypothesis H_0 that $\{X_t\}$ does not Granger cause $\{Y_t\}$ is equivalent to testing conditional independence of Y_{t+1} on the past values of X_t, given the past values of Y_t. That is,

$$Y_{t+1} \left| \left(X^{L_X}_t; Y^{L_Y}_t\right) \sim Y_{t+1} \right| Y^{L_Y}_t \tag{5}$$

where $X^{L_X}_t = (X_{t-L_X+1}, \ldots, X_t), L_X = 1, 2, \ldots t$ is the L_X-length lag vector of X_t, and $Y^{L_Y}_t = (Y_{t-L_Y+1}, \ldots, Y_t), L_Y = 1, 2, \ldots, t$ is the L_Y-length lag vector of Y_t. '~' denotes equivalence in distribution. For a strictly stationary time series, Eq. (5) is simply a statement of the invariant distribution of the (L_X+L_Y+1)-length vector $W_t=(X_t^{L_X},Y_t^{L_Y},Z_t)$, where $Z_t=Y_{t+1}$. To keep notation compact, we drop the time index and just denote $W=(X,Y,Z)$. To motive the test statistic, it is convenient to restate the null in terms of ratios of joint distributions. Diks and Panchenko (2006) shows that the null implies:

$$E\left[\left(\frac{f_{X,Y,Z}(X,Y,Z)}{f_Y(Y)}-\frac{f_{X,Y}(X,Y)}{f_Y(Y)}\frac{f_{Y,Z}(Y,Z)}{f_Y(Y)}\right)g(X,Y,Z)\right]=0 \tag{6}$$

where $f(\cdot)$ represents the probability density function, and $g(\cdot)$ is a positive weight function. Intuitively, under the null hypothesis the term within the round brackets of Eq. (6) vanishes, leaving the expectation to be zero. Regarding the choice of $g(\cdot)$, Monte Carlo simulations suggest $g(X,Y,Z)=f_Y^2(y)$. Given such a choice, Eq. (6) is reduced to

$$E[(f_{X,Y,Z}(X,Y,Z)f_Y(Y)-f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)]=0. \tag{6'}$$

To estimate those density functions in Eq. (6), note that a local density estimator of a d_W-dimensional vector W at W_i can be written as

$$\hat{f}_W(W_i)=\frac{(2\varepsilon)^{-d_W}}{n-1}\sum_{j,j\neq i}I_{ij}^W \tag{7}$$

where $I_{ij}^W=I(||W_i-W_j||<d)$; $I(\cdot)$ is the indicator function (equals 1 when the statement of interest is true; otherwise 0); $||\cdot||$ is the maximum norm, which for a m-dimensional vector $z=(z_1,z_2\ldots,z_m)$ is defined as $\max(z_m), i=1,2,\ldots,m$; d is bandwidth — an arbitrarily small positive constant; n is the sample size. Given Eq. (7), a natural test statistic for Eq. (6) takes the form:

$$T(d)=\frac{(n-1)}{n(n-2)}\sum_i[\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\hat{f}_Y(Y_i)-\hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)]. \tag{8}$$

So the test statistic is simply a weighted average of local contributions $\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\hat{f}_Y(Y_i)-\hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)$, which tend to be zero under the null hypothesis. By allowing the bandwidth d to depend on sample size n, more specifically, $d_n=Cn^{-\beta}$ where $C>0,\beta\in(1/4,1/3)$, Diks and Panchenko (2006) show that the test statistic is asymptotically normally distributed:

$$T(d_n)\sim N\left(0,\frac{\sigma^2}{n}\right) \tag{9}$$

where σ^2 is the asymptotic variance of the test statistic.[1]

2.2.2. Measuring the strength of nonlinear causality

The test statistic in Eq. (8) can only be used as a diagnostic tool for nonlinear causality. In this section, we show how to measure the causality strength through the use of nonparametric regression models (Song and Taamouti, 2013).

Consider the following two nonparametric regressions:

$$\text{Unrestricted}:\quad X_{t+1}=\Phi(Q_t)+u_{t+1} \tag{10}$$

$$\text{Restricted}:\quad X_{t+1}=\overline{\Phi}(X_t)+\overline{u}_{t+1} \tag{11}$$

where $Q_t=(X_t,Y_t)'$, $\Phi(\cdot)$ and $\overline{\Phi}(\cdot)$ are nonparametric functions, u and $\overline{u}$ are error terms. Eq. (11) is labeled as 'restricted' because Y_t is absent.

[1] The asymptotic variance is estimated using the methodology of U-statistic of Powell and Stoker (1996). For a complete and detailed derivation of the variance see the appendix in Diks and Panchenko (2006).

Given the two regressions, the strength of nonlinear causality from Y to X can be measured as:

$$C_{Y\to X}=\ln(Var(\overline{u}_{t+1})/Var(u_{t+1})). \tag{12}$$

It is easy to see that Eq. (12) follows the same spirit as in the linear case by using the log ratio of the variance of error terms to measure causality strength. The difference is that Eq. (12) is estimated from nonparametric regressions, which can accommodate the unknown nonlinear functional form between X and Y. To implement Eq. (12), we use the popular Nadaraya–Watson kernel estimator (Nadaraya, 1964; Watson, 1964) to carry out the nonparametric regressions. More specifically, we have

$$\text{Unrestricted}:\quad \Phi(q)=\sum_{t=1}^{n}N_t(q,h)X_t \tag{13}$$

$$\text{Restricted}:\quad \overline{\Phi}(x)=\sum_{t=1}^{n}\overline{N}_t\left(x,\overline{h}\right)X_t \tag{14}$$

where $q=(x,y)'$; $N_t(q,h)=k(\frac{x-X_{t-1}}{h})k(\frac{y-Y_{t-1}}{h})/\sum_{s=1}^{n}[k(\frac{x-X_{s-1}}{h})k(\frac{y-Y_{s-1}}{h})]$; h is the bandwidth for unrestricted regression; $\overline{N}_t(x,\overline{h})=k(\frac{x-X_{t-1}}{\overline{h}})/\sum_{s=1}^{n}k(\frac{x-X_{s-1}}{\overline{h}})$; $\overline{h}$ is the bandwidth for restricted regression; $k(\cdot)$ is a univariate kernel function. Given Eqs. (13)–(14), we can derive the variance of error terms:

$$\text{Unrestricted}:\quad Var(\hat{u}_{t+1})=\frac{1}{n}\sum_{t=1}^{n}(X_t-\hat{\Phi}(Q_{t-1}) \tag{15}$$

$$\text{Restricted}:\quad Var\left(\hat{\overline{u}}_{t+1}\right)=\frac{1}{n}\sum_{t=1}^{n}(X_t-\hat{\overline{\Phi}}(X_{t-1}). \tag{16}$$

Based on Eqs. (15)–(16), we can use Eq. (12) to quantify the degree of nonlinear causality.

3. Data

As mentioned before, we use data of 5-minute frequency. This frequency level is believed to be an appropriate choice to minimize the adverse effect of market microstructure frictions (e.g. Andersen et al., 2003; Bollerslev et al., 2006). Even though data of this frequency are readily available for individual real estate security through popular data platforms like Trades & Quotes (TAQ), we want to perform a market-level analysis. To this end, Bloomberg seems to be the only source from which we can get the data needed. Bloomberg provides intraday price data for the well-known FTSE EPRA/NAREIT U.S. Index. This index incorporates a variety of listed real estate companies (e.g. Real Estate Investment Trusts (REITs), real estate holding and development companies) whose shares are traded on New York Stock Exchange (NYSE). The index is designed to track the performance of securitized real estate in the U.S. market. As argued in Bond et al. (2003), it has become a benchmark index for analyzing real estate securities markets. We collect data from Jan 2008 to Dec 2014, and compute 5-min return as the difference between consecutive logarithm 5-min closing prices. We then measure volatility using the popular realized variance (RV) estimator defined as follows (Andersen et al., 2001):

$$RV=\sum_{i=1}^{m}r_i^2. \tag{17}$$

RV is shown to be a consistent estimator of the true volatility (refer to Chp 13 of Bauwens et al., 2012). Note that m is the number of 5-min intervals within a certain time period. Given the regular trading hours [9:30–16:00] of NYSE, we have $m=78$ for most days in our sample. However, some trading days have $m<78$, due to delayed openings and/or early closings of the exchange. If we focus on a finer frequency, say, 1 h, then $m = 12$. Using the raw 5-min data as building blocks, we choose to carry out the investigation at four levels of sampling frequency: 15 min ($m = 3$), 30 min ($m = 6$), 1 h ($m = 12$), and 1 day ($m = 78$ for most days).[2] The corresponding return of each frequency will be constructed by summing m successive 5-min returns.

Table 1 reports the summary statistics. The mean return is positive across different sampling frequencies. As expected, volatility becomes higher for a higher level of temporal aggregation. Across both panels, both return and volatility display significant skewness and kurtosis. Finally, based on the results of break-point-robust unit root tests of Popp (2008) and Narayan and Popp (2010, 2013), both return and volatility are stationary. This holds for all sampling frequencies under study. As will be discussed below, this result has important implications for the VAR modeling. Fig. 1 plot the REIT return and volatility sampled at the four frequencies over 2008–2014. Clearly, volatility has a clustering property where periods of high volatility or low volatility can remain persistent for some time before switching. The most pronounced spike of high volatility occurred in some early part of the data sample. This is obviously due to the recent 2008–09 global financial crisis.

Table 1
Summary statistics.

	Obs #	Mean	Std. dev.	Skewness	Kurtosis	*Popp* test	*NP* test
Panel a: Return							
15 min	46,346	0.0005	0.404	0.042*	29.619*	−52.970*	−52.978*
30 min	23,173	0.001	0.570	0.087*	22.440*	−40.403*	−40.996*
1 h	11,586	0.002	0.822	0.294*	20.678*	−30.086*	−30.842*
1 day	1774	0.013	2.644	−0.200*	10.348*	−17.565*	−17.580*
Panel b: Volatility							
15 min	46,346	0.157	0.713	19.498*	719.414*	−16.415*	−16.465*
30 min	23,173	0.314	1.171	14.003*	352.310*	−13.491*	−13.533*
1 h	11,586	0.629	1.945	9.479*	147.860*	−14.760*	−14.842*
1 day	1774	4.109	8.423	4.649*	31.932*	−4.586*	−4.705*

Notes: This table reports the summary statistics for U.S. REIT return and volatility from 2008 to 2014. The volatility is measured using the realized volatility estimator of Andersen et al. (2001). *Popp* test is the structural break unit-root test of Popp (2008), which assumes one break while *NP* test is the structural break unit-root test of Narayan and Popp (2010, 2013), which assumes two breaks. The null hypothesis of both tests is a unit root. We generate the test statistics by assuming endogenous (unknown) break(s) and allowing for a change in both the level and slope of time series. Both tests reject the null of unit root for return and volatility, as the test statistics presented are well above (in terms of absolute value) the 5% critical values as shown in the above two papers.
* Significant at 5% level.

4. Empirical findings

4.1. Linear causality

As mentioned earlier, the return and volatility series are stationary. Thus, it is appropriate to build a VAR model in levels (i.e. Eqs. (1) & (2)). We then estimate the VAR to check out linear Granger causality. Table 2 reports the results. We find that the *F*-statistic is significant in all cases, suggesting that both leverage effect ($r \rightarrow \sigma^2$) and volatility feedback effect ($\sigma^2 \rightarrow r$) are at work. Furthermore, we find that the relative strength of the two effects appear to be dependent upon the sampling frequency under study. For example, the leverage effect clearly dominates the volatility feedback effect at the frequency level of 30-min, 1-hour, and 1-day while the two effects are approximately of equal strength at the 15-min level. However, at this stage, it would be premature to conclude that these results reflect the true causal links between REIT return and volatility, as we are not sure if the interactions between return and volatility would occur in a more subtle (i.e. nonlinear) fashion. The nonlinear results, if nonlinear causality is confirmed, may be different than these linear results. This is the subject of the next section.

4.2. Nonlinear causality

Before testing for nonlinear Granger causality, it is informative to start with a check of whether the data are characterized by nonlinearities. We perform a nonlinear dependence test known as the Brock et al. (1987) (*BDS*) test. *BDS* essentially tests for deviations from identically and independently distributed (*i.i.d.*) behavior in time series.[3] The test results, not tabulated here but available upon request, reveal that the *BDS* statistic is statistically significant for return and volatility across all data frequencies, indicating the presence of nonlinearity in the data.

To implement the diagnostic test discussed in Section 2.2.1, we must first select the bandwidth d_n, and lag lengths L_X and L_Y. Following Diks and Panchenko (2006), we set $d_n = 8n^{-2/7}$ (n is the sample size). For the lag length, we set $L_X = L_Y$ and use common lag lengths of one to four. We then apply the diagnostic test to the residuals from the linear VAR model. The results are presented in Table 3. There are two salient points: first, the test statistic T is significant for all cases of the leverage effect ($r \rightarrow \sigma^2$) and for all but one cases of the volatility feedback effect ($\sigma^2 \rightarrow r$). This finding suggests strong bi-directional nonlinear causality. It implies that both leverage and volatility feedback effects exist in the U.S. REIT market, and they take place in a nonlinear fashion. Second, both leverage and volatility feedback effects are found to be highly persistent. The reasons is that as we extend the lag length of $L_X = L_Y$ from one to four, T statistics generally remain large and significant (Diks and Panchenko, 2006).

To assess the strength of both effects, we utilize the nonparametric regression models outlined in Section 2.2.2. The first thing is to choose a kernel function $k(\cdot)$ and bandwidth (h & $\bar{h}$) (see Eqs. (13)–(14)). As is well understood in the nonparametric literature, the choice of the bandwidth is much more important than that of the kernel function (Chp 1 of Li and Racine, 2007). As such, we utilize a technique called cross-validation to determine the optimal bandwidth (refer to Chp 2 of Li and Racine (2007) for more technical details) and simply use the popular Gaussian kernel. Table 4 reports the results. We find that the leverage effect overwhelmingly dominates the volatility feedback effect across all four sampling frequencies under study. The results, compared with what is reported based on the linear specification, show some clear differences. For instance, the linear results using the 15-min data indicate equal strength for the two effects but once nonlinearity is accounted for, the leverage effect is found here 127 times stronger than the volatility feedback effect. For the other three sampling frequencies, nonlinear results show a higher degree of dominance of the leverage effect over the volatility feedback effect than does the linear results. For example, at the 30-min level, here the leverage effect is 19.4 times stronger than the volatility feedback effect but before merely 4.4 times. The same pattern holds when 1-hour and 1-day data are employed.

To sum up, our results add new evidence to the literature.[4] First, both leverage and volatility feedback effects are at work in U.S. REIT market. This finding is consistent with some stock studies. For example, Wu (2001) find that both the leverage effect and volatility feedback effect are important determinants of asymmetric volatility in U.S. stock market. Second, both leverage and volatility feedback effects are nonlinear.

[2] The 5-min returns are being used as building blocks. Following Eq. (17), we can only use them to construct volatility time series for lower-level frequencies (15-min, 30-min, and so on). This is why we do not test the hypotheses at the 5-min data level.

[3] See p 185 of Tsay (2005) for more explanations.

[4] The results remain qualitatively similar when we use the log transformation of the volatility – $\ln(\sigma_t^2)$ and an alternative volatility measure – realized range (Christensen and Podolskij, 2007). We also show that, by decomposing *RV* into a continuous component (bipower variation), and a jump component (e.g. Bollerslev et al., 2009), the asymmetry between return and volatility works primarily through the continuous component, not the jump component. To save space, those results are not presented but available upon request.

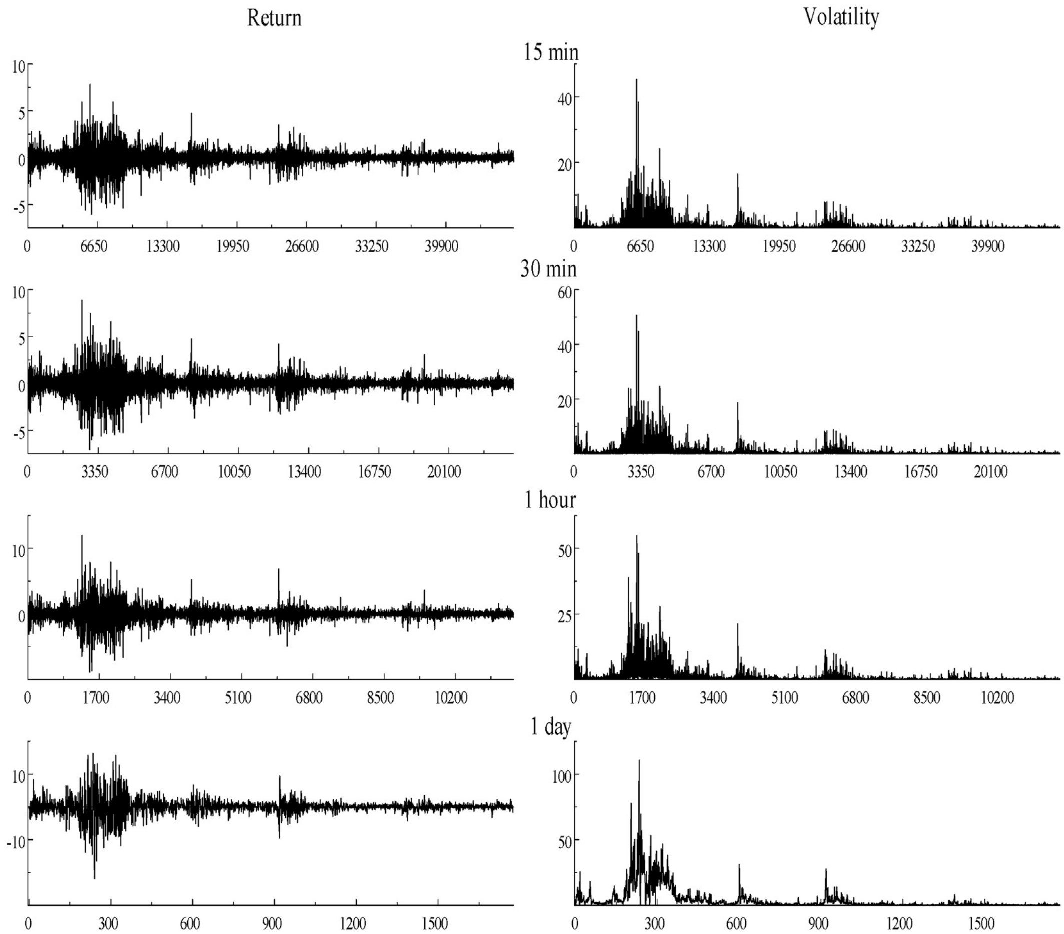

Fig. 1. Plots of U.S. REIT return and volatility over the sample period of 2008–2014.

Considering there is no theoretical justification for the effects to be linear, this casts doubt upon those studies focusing only on a linear relationship, and adds to the extremely thin literature on the potentially nonlinear causality between return and volatility (e.g. Bouezmarni et al., 2012). Third, the leverage effect prevails. A plausible reason for this finding is due to REITs' relatively large use of leverage (Case et al., 2012; Yang et al., 2012). REITs are required by Internal Revenue Service (IRS) enabling rules to pay out at least 90% of taxable income as dividends. Retaining little earnings and being capital intensive, many REITs turn to debt. Our finding of the dominance of leverage effect is in line with those of the stock studies of Bollerslev et al. (2006), Masset and Wallmeier (2010), and Dufour et al. (2012), but in contrast to those of Bekaert and Wu (2000) and Dennis et al. (2006).

Table 2
Results of linear Granger causality tests.

Data	Direction	F-statistic	p-Value	Causality strength
15 min	$r\to\sigma^2$	4.593*	0.000	0.020
	$\sigma^2\to r$	5.321*	0.000	0.023
30 min	$r\to\sigma^2$	31.706*	0.000	0.022
	$\sigma^2\to r$	7.047*	0.000	0.005
1 h	$r\to\sigma^2$	29.434*	0.000	0.049
	$\sigma^2\to r$	5.885*	0.000	0.010
1 day	$r\to\sigma^2$	11.770*	0.000	0.129
	$\sigma^2\to r$	5.279*	0.000	0.059

Notes: This table reports the results of linear Granger causality tests. The lag length used in the test is determined by Bayesian Information Criterion (BIC). The notation A → B means that A Granger causes B. $r\to\sigma^2$ represents the leverage effect and $\sigma^2\to r$ represents volatility feedback effect.

* Significant at 5% level.

Table 3
Diagnostic testing of nonlinear Granger causality.

$L_X=L_Y$	$r\to\sigma^2$		$\sigma^2\to r$	
	T	p-Value	T	p-Value
15 min				
1	28.209*	0.000	14.171*	0.000
2	23.191*	0.000	7.347*	0.000
3	19.476*	0.000	3.502*	0.000
4	16.528*	0.000	0.579	0.281
30 min				
1	20.543*	0.000	14.045*	0.000
2	17.275*	0.000	9.740*	0.000
3	13.948*	0.000	7.060*	0.000
4	12.221*	0.000	5.312*	0.000
1 h				
1	15.121*	0.000	12.200*	0.000
2	12.571*	0.000	8.943*	0.000
3	10.652*	0.000	6.539*	0.000
4	9.424*	0.000	4.785*	0.000
1 day				
1	8.210*	0.000	7.287*	0.000
2	8.656*	0.000	5.612*	0.000
3	7.674*	0.000	4.577*	0.000
4	6.547*	0.000	4.295*	0.000

Notes: This table reports the results of nonlinear Granger causality using the nonparametric test of Diks and Panchenko (2006). T is the test statistic of nonlinear causality in Eq. (8). The notation A → B means that A Granger causes B. $r\to\sigma^2$ represents the leverage effect and $\sigma^2\to r$ represents volatility feedback effect. $L_X=L_Y$ denotes the number of lags used in the lag vectors of Eq. (5). The bandwidth $d_n=8n^{-2/7}$ (n is the sample size).

* Significant at 5% level.

Table 4
Strengths of nonlinear causality.

Data	Direction	Optimal bandwidth $\bar{h}$	h	Causality strength
15 min	$r \to \sigma^2$	0.055	0.050	0.894
	$\sigma^2 \to r$	5.500	5.009	0.007
30 min	$r \to \sigma^2$	0.909	1.680	0.136
	$\sigma^2 \to r$	5.550	5.550	0.007
1 h	$r \to \sigma^2$	0.639	0.050	1.668
	$\sigma^2 \to r$	2.484	5.550	0.001
1 day	$r \to \sigma^2$	0.521	0.059	2.031
	$\sigma^2 \to r$	2.625	2.756	0.068

Notes: This table reports the estimated strength of nonlinear causality using the nonparametric regressions specified in Eqs. (12)–(16). $\bar{h}$ & h are the optimal bandwidth estimated from cross validation for the restricted and unrestricted models, respectively. The notation A → B means that A Granger causes B. $r \to \sigma^2$ represents the leverage effect and $\sigma^2 \to r$ represents volatility feedback effect.

4.3. Potential sources of nonlinearity

Given the above findings, a natural question arises: what are the causes for nonlinearity? Answering the question would help us gain a better understanding of the dynamic return–volatility relationship. The voluminous literature on the nonlinearity of time series suggests a few candidates: regime switching (Ang and Timmermann, 2012), structural breaks (Koop and Potter, 2001), and outliers (van Dijk et al., 1999). All of them arise from the tendency of the financial market to often change its behavior. Regime switching refers to the case where dynamic properties vary over the state of market. This change is recurring and to a certain degree predictable. Structural break, on the other hand, refer to the case where the dynamics change permanently in a way that cannot be predicted by the history of the series. Outliers refer to shifts in the level of a time series that are inconsistent with the remainder of the series. Outliers are also unpredictable. But unlike structural breaks, they have only temporary impacts on the dynamics.

Table 5 reports the testing results for the three possible causes.[5] To test for regime switching, we adopt the idea of Markov switching of Hamilton (1989) and augment the linear VAR of Eqs. (1)–(2) by making the parameters regime-dependent:

$$\mathbf{Y}_t = \boldsymbol{\alpha}_{s_t} + \boldsymbol{\beta}_{1,s_t}\mathbf{Y}_{t-1} + \cdots + \boldsymbol{\beta}_{p,s_t}\mathbf{Y}_{t-p} + \boldsymbol{\varepsilon}_t \quad (18)$$

where $\mathbf{Y}_t = (r_t, \sigma_t^2)'$, $\boldsymbol{\varepsilon}_t \sim N(0, \Sigma_{s_t})$, and p is the lag length to be determined by *BIC*. For simplicity, we allow two regimes ($s_t = 1$ or 2) and assume the regime evolution follow a first-order Markov chain: $\Pr(s_t = j/s_{t-1} = i) = p_{ij}$ with $i, j = 1$ or 2. The results, presented in Panel a, show strong evidence for regime switching.[6] As revealed by the estimated standard deviations of return residuals, regime 1 is tranquil ($\sigma_{1,1}$ is small) while regime 2 is volatile ($\sigma_{1,2}$ is large). Both regimes are persistent, as the regime staying probabilities p_{11} and p_{22} are found large. Furthermore, the tranquil regime 1 lasts longer than the volatile regime 2, based on the estimated expected duration of regime (ψ_i).

To test for structural breaks, we resort to the Weighted Double maximum test proposed by Qu and Perron (2007). This test is particularly suitable for a VAR system involving multiple regressions (Eqs. (1)–(2)) and useful to determine whether some structural breaks take place. This is in contrast to most available structural-break-detection techniques which can be applied only to single-equation regressions. This test considers the null hypothesis of no break versus the alternative hypothesis of some unknown number of breaks. Panel b presents the test results. We find strong evidence of structural breaks occurring in the VAR system.

To check the presence of outliers, we consider additive outlier (AO) — one of the basic types of outliers defined by Fox (1972). By definition, *AO* affects only a single observation. We then utilize the procedure of Chen and Liu (1993) to identify *AO* for return and volatility. Panel c shows that there are a fairly large number of *AO* occurring in return and volatility.

Table 5
Checking the potential sources of nonlinearity.

	15 min	30 min	1 h	1 day
Panel a: Regime switching				
$\sigma_{1,1}$	0.28(0.00)*	0.42(0.00)*	0.59(0.00)*	2.19(0.00)*
$\sigma_{1,2}$	1.17(0.00)*	1.49(0.00)*	2.37(0.00)*	26.42(0.00)*
p_{11}	0.90(0.00)*	0.89(0.00)*	0.89(0.00)*	0.96(0.00)*
p_{22}	0.75(0.00)*	0.69(0.00)*	0.71(0.00)*	0.89(0.00)*
ψ_1	10.51	8.96	8.73	22.51
ψ_2	3.96	3.28	3.50	9.31
Panel b: Structural breaks				
*WD*max	297.29*	236.01*	164.57*	57.51*
Panel c: Outliers				
Returns	47	36	14	8
Volatility	91	74	30	10

Notes: This table reports the testing results for the potential sources of nonlinearity present in the causality results. The results are based on the data of the year 2008. $\sigma_{1,i}$ is the estimated standard deviation of return residuals in regime i (1 or 2). p_{ii} is the estimated regime ($i = 1$ or 2) staying probabilities. For both $\sigma_{1,i}$ & p_{ii}, p-value is in parenthesis. ψ_i is the expected duration of the regime ($i = 1$ or 2) conditional on being in this regime. *WD*max is the Weighted Double maximum test of structural break(s) of Qu and Perron (2007). The statistic reported here is of the 5% level, for which the corresponding critical value is 21.09. The outlier examined here is additive outlier (AO) — an unusual innovation affecting only a single observation. We report the number of significant *AO* detected over 2008 using the tests of Chen and Liu (1993).
* Significant at 5% level.

4.4. Implications

First, our finding leads to a better understanding of the recent movement of REIT volatility. It is well observed that during the 2007–09 financial crisis REIT prices plummeted and volatilities skyrocketed even above the level of the general stock market (Yang et al., 2012). This unprecedented phenomenon has impacted the long-held perception of REITs as a safe-haven investment (e.g. high yield and low volatility). With our findings here, the phenomenon is not as puzzling as it appears at first glance. We know that due to the high payout rule, REITs are more dependent on short-term liquidity sources than companies in other sectors. This, coupled with the low and declining interest rates in the early 2000s, made REITs highly levered relative to other types of firms (Giacomini et al., 2015). At the onset of the crisis, price declined, which, through the high leverage effect, would induce a large volatility increase. Since the volatility feedback effect is also at work, price would further decline. The outcome of this process is that REITs experienced a bout of uncharacteristically high volatility (the bout can be clearly seen in Fig. 1). This twist caused enormous concerns and turned away some people (e.g. risk-averse investors and fixed-income managers) who had traditionally invested in REITs. After the crisis period REIT volatility decreased and appeared to be stabilized over time. Two reasons are worth noting: one is that REITs have de-levered notably (Kawaguchi et al., 2012), and the other is that REIT prices have recovered. Price increase implies a decrease in volatility, according to the leverage effect (though the magnitude of effect would be reduced compared with its peak level during the crisis). Due to the volatility feedback effect, a decrease in volatility would further contribute to price recovery.

[5] To reduce computational burden, we only do the testing using the data of 2008. Using a longer data sample only leads to higher and more significant test results.

[6] To complement the results here, we also employ the test of Cho and White (2007) for regime switching. Consider a simple model for returns (e.g. Kasahara et al., 2014): $r_t = \pi \cdot N(\mu_1, \sigma_1^2) + (1-\pi) \cdot N(\mu_{21}, \sigma_2^2)$. Testing the null of no regime switching in expected returns leads to test statistics in the neighborhood of 60.000 for return series sampled at various frequencies (15-min, 30-min, 1 h, & 1 day). The test statistics are way greater than the critical values reported in Cho and White (2007). Therefore we confirm the existence of regime switching in returns. For volatility, the test statistics are even larger. So regime switching in volatility also exists.

Second, our findings can help improve asset pricing. In the financial literature, there is ample mixed evidence for the sign of the supposedly positive risk–return trade-off (e.g. Bollerslev et al., 1988; Glosten et al., 1993; Nelson, 1991, etc.). One possible reason is due to the implicit assumption of a linear risk–return relation. Such an assumption is rather restrictive, and probably does not hold in practice. This point is confirmed here as our results underscore the existence of nonlinearity in the return-volatility dynamics. As such, ignoring nonlinearity would lead to a mis-specified risk–return relation and confounding evidence. As a matter of fact, some papers (e.g. Christensen et al., 2012) have suggested tackling this issue by using an asset pricing model with general nonparametric risk–return specification. We believe this constitutes a valuable direction for future research. It would be worthwhile to see how much we can improve asset pricing by considering nonlinearity for the REIT sector.

5. Conclusion

One of the stylized facts in finance is that equity returns and volatility are negatively correlated. This is often referred to as asymmetric volatility in the literature. Two alternative explanations have been proposed: the leverage effect hypothesis explains why a negative (positive) return causes a higher (lower) subsequent volatility, while the volatility feedback hypothesis justifies how an anticipated increase (decrease) in volatility causes a negative (positive) return. Drawing upon the concept of Granger causality, this paper makes the first attempt in the real estate literature to test the two hypotheses.

Our findings suggest that both effects are at work and highly persistent in the U.S. REIT market. More importantly, both are nonlinear. Multiple sources (e.g. regime switching, structural breaks, outliners) are found to contribute to the existence of nonlinearity. In addition, we find that the leverage effect dominates the volatility feedback effect. The above results are robust to data sampling frequencies. Our findings have important implications. They deepen our understanding of the recent movement of REIT volatility, and moreover, the finding of nonlinearity is expected to better capture the risk–return trade-off and have profound impacts on asset pricing.

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