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Time-Varying Correlations of REITs and Implications for Portfolio Management

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ABSTRACT

This study uses bivariate dynamic conditional correlations (DCC) to analyze REITs' relation with stock and bond markets from 1999 to 2018. The results show that the daily DCCs of both Equity REIT and Mortgage REIT returns experienced several structural changes attributed to the state of the economy, levels of leverage, inclusion or exclusion of REITs from the major S&P indices, and REITs getting their own Global Industry Classification Standard (GICS) category. To account for the structural changes, we allow the impact of the macroeconomic driving forces of the DCCs to vary over time. First, we formulate an OLS model using dummy variables regression (DV) to indicate regime membership, using endogenous break-dates. Then, we estimate a Markov regime-switching model (MRS) that allows the impacts of macroeconomic variables to differ during high and low variance regimes. Both complementary regime-sensitive models (DV and MRG) exhibit significant improvement relative to a traditional OLS model. The findings have significant implications for portfolio and risk management. For example, we find that with the new GICS sector, Equity REIT returns decoupled from the Financial Sector and the overall market as measured by the SP 500. These types of correlation shifts can significantly alter optimal portfolio weights whether trying to maximize returns, minimize risk, or achieving the highest risk-adjusted returns.

KEYWORDS
Structural changes; REITs; portfolio rebalancing; Markov-regime switching; dynamic conditional correlations

Understanding the time-varying correlations among major asset classes is vital for active asset allocation, risk management, and hedging. To this end, we investigate the time-varying nature of correlations between the REIT markets and the equity (SP500) and bond markets. Our study documents many structural shifts (sub-periods characterized by different dynamic relations) generated by the state of the economy, levels of leverage, the inclusion or exclusion of REITs from the major S&P indices, and the new Global Industry Classification Standard (GICS) sector. While time-varying correlations can be explained by the small set of macroeconomic variables introduced by Yang et al. (2012) (i.e., default spread, term spread, mortgage spread, and the VIX), we more than double

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the Yang et al. (2012) sample period and allow the estimated intercepts and coefficients of these explanatory variables to vary across sub-periods when the dynamic correlations exhibit a structural shift. We combine two estimation methods to allow the impact of macroeconomic driving forces to change over time: an OLS model with dummy variables (DV) to indicate regimes detected by a prior endogenous test, and a Markov regime-switching (MRS) model.

Compared with a simple OLS regression without regimes, our collective approach combines MRS and DV models to significantly improve the performance of the REITs' DCCs as measured by R^2, log-likelihood, AIC, and SBC. Although the DV model outperforms the MRS model, we believe the two are complementary. The DV models' performance depends strongly on the structural breaks' prior specification, so its metrics overestimate the model's performance. In the absence of prior knowledge to specify the regime breaks, we expect MRS to outperform DV around the breaks' dates. Thus, we propose researchers estimate both models simultaneously and use the DV model until its performance deteriorates around a structural break. Then, the MRS model can be primarily relied upon until the structural breaks are identified. This unified approach to modeling the DCCs has important implications for optimal portfolio allocations and the pricing of real estate derivatives. Although it is beyond the scope of this article, we ran optimal portfolios using the identified correlation breaks and computed the returns and risk over the sample period. The results created better portfolio outcomes.

Literature Review

Many studies have examined the time-varying correlations between the REIT markets and the bond and stock markets. For example, Case et al. (2012) use a generalized autoregessive conditional heteroskedasticity (DCC-GARCH) model to show that between September 2001 and September 2008, the dynamic correlation between the REIT market and the stock market gradually increased from 30% to almost 60%. This increase was initiated by the inclusion of REITs in the S&P 500 and other broad stock market indices in 2001. However, the dynamic correlation between the REIT and bond markets fluctuated over the same period within 15.0% to 20.5%. Wurgler (2010) and Pavlov et al. (2018) attribute the increased correlation to the liquidity effect, wherein all stocks of the S&P 500 are subject to a similar trading strategy. As a result, all stocks of the S&P 500 might be exposed to the same capital inflows and outflows. Furthermore, Pavlov et al. (2018) find that REITs' inclusion has improved pricing efficiency and strengthened the correlations between REITs and their underlying real estate assets.

Kawaguchi et al. (2017) provide an intuitive explanation for the stronger relation between REIT and stock prices during the Great Recession. They state that during Greenspan's era, the Federal Reserve Bank successfully stabilized inflation and lowered the risk premium through its commitment to providing liquidity and reducing short-term interest rates during recessions. Consequently, the Fed decreased the long-term interest rate, which is the sum of expected inflation, expected real short-term interest rates, and a term premium. Through the non-neoclassical bank capital channel, the lower interest rate strengthened the banks' loan portfolios and increased their supply of loans. Given the strong tendency of REIT companies to borrow, and the large supply of loans with low-interest rates, REITs experienced relatively high leverage ratios before the Great Recession. However, when the financial crisis started, the market experienced a high-risk premium and scarcity in the refinancing option. Consequently, both stock and REIT markets suffered a considerable price decrease, significantly increasing the correlations between their returns. Another contributor to this effect is the increase in the REIT and equity markets' risk premium during a recession, which directly decreases their prices.

Chong et al. (2009) find that the relation between the REIT market and the bond market is strong and negative during high volatility in the bond market. Furthermore, Alcock and Steiner (2018) confirm that REITs' excessive tendency to borrow increases the likelihood of negative return clustering between REITs and stocks. Yang et al. (2012) measure a negative (positive) correlation between the REIT market and the bond market (stock market) during recessionary periods. They attribute their finding to the dominance of the cash flow effect during recessions. Yang et al. (2012) also demonstrate that current and future business conditions and volatility, as captured by default spread, term spread, mortgage spread, and stock market volatility, are driving forces of REITs' time-varying correlations with both the stock and bond markets. Chong et al. (2012) utilize the GARCH-DCC framework to estimate the dynamic correlations between REIT sub-sectors between 1990 and 2008. They show that correlations among the sub-sectors have been continually increasing since 1990. Thus, the diversification advantage from investing in different REIT sub-sectors has decreased over the same period.

In a recent study using very similar statistical techniques but with a different research focus, Hardin et al. (2020) examine the impact that being included in an exchange-traded fund (ETF) has on volatility in underlying assets. Using non-U.S. data, the authors find that the benefits of being able to achieve a diversified portfolio of real estate assets likely outweighs the slight increased risk caused by them being more heavily traded in the ETF marketplace.

Data

The data in this paper consist of end-of-day closing prices for the following indices: FTSE NAREIT Equity REITs ("Equity REIT"), FTSE NAREIT Mortgage U.S. REITs ("Mortgage REIT"), S&P 500 ("SP500"), Bloomberg Barclays US AGG ("Bond"), and S&P Financials ("SP500 Financials") and cover the period from 1999:03:02 to 2018:12:26. Yang et al. (2012) cover just over nine years, while our dataset extends nearly 20 years.[1]

Understanding the driving forces of the time-varying correlations between markets is crucial for asset allocation and risk management. As such, we follow Yang et al. (2012) in selecting four candidates: the default spread (DEF), the term spread (TERM), the mortgage spread (MGTB), and the Chicago Board Options Exchange S&P500 volatility index (VIX). DEF is the difference between the Moody BAA and AAA bond yields. The magnitude of the default spread increases when the economic environment deteriorates, notably during recessions and other financial stress episodes. Thus, the default spread may widen or narrow-based on the state of the economy. The term spread (TERM) is the difference between the 10-year and 3-month treasury yields. TERM (or, more generally, the yield curve) is a widely recognized indicator of economic health. Over the past 30 years, every recession was preceded by an inverted yield curve where the 3-month Treasury

Table 1. Descriptive statistics of the financial indices and the macroeconomic determinants.

	Minimum	Mean	Maximum	Variance	Reward/Risk	Skewness	Kurtosis	J.B. stat
$REIT_E$	−21.532	0.0383	16.8783	3.115	0.0217	−0.2099***	21.817***	98247***
$REIT_M$	−19.1933	0.0256	24.6812	2.8283	0.0152	0.3340***	33.489***	231508***
SP500	−9.4595	0.0216	10.4252	1.4601	0.0179	−0.2530***	8.1579***	13785***
Bond	−1.2621	0.0182	1.3258	0.0545	0.0778	−0.1491***	1.5403***	507.87[3***]
SP500 Financials	−18.639	0.0034	17.2013	3.6769	0.0018	−0.0196	16.4033***	55518***
Moody BAA	4.15	6.2143***	9.54	1.6448	4.8455	0.2839***	−1.003***	274***
AAA Bond	3.18	5.1783***	8.12	1.475	4.2637	0.4132***	−0.737***	253***
Default Spread	0.51	1.0359***	3.5	0.1863	2.4000	3.0457***	11.65***	35706***
Ten-Year TB	1.37	3.5984***	6.79	1.6715	2.7833	0.2551***	−0.926***	231***
Three-Month TB	−0.02	1.7399***	6.24	3.554	0.9229	0.8801***	−0.622***	719***
Term-Spread	−0.77	1.8585***	3.87	1.1641	1.7225	−0.2536***	−0.766***	174***
Thirty-Year Mortgage	3.32	5.2038***	8.38	1.4442	4.3302	0.4876***	−0.502***	248***
Thirty-Year TB	2.11	4.2201***	6.75	1.1516	3.9325	−0.0193	−1.141***	269***
Mortgage Spread	−0.2031	0.9837***	2.74	0.1861	2.2803	0.5576***	0.838***	402***
VIX	9.14	19.8522***	80.86	71.5213	2.3474	2.0685***	7.220***	14290***

Notes. This table presents the descriptive statistics of the daily returns on equity REIT ($REIT_E$), Mortgage REIT ($REIT_M$), SP500, Bloomberg Barclays US AGG (Bond), SP500 Financials, the default spread (DEF). The table also the descriptive statistics of the presents the term spread (TERM), the mortgage spread (MGTB), and the Chicago Board Options Exchange S&P500 volatility index (VIX). All series are daily and cover the period from1999:03:02 to 2018:12:26. The null hypothesis for the Jarque-Bera test is that the data are normally distributed. The number between parentheses is the p-value of the null hypothesis that the statistics are not statistically different from zero.
*, **, *** denote significance levels at 10%, 5%, and 1%, respectively.

yield exceeded the 10-year yield. MGTB is the difference between the 30-year mortgage rate and the 30-year Treasury bond yield. Yang et al. (2012) posits that MGTB is the best available macroeconomic proxy for the real estate sector. Finally, VIX reflects the overall near-term market risk implied by the options market.

Table 1 provides descriptive statistics for the daily, continuously compounded returns on all these series over the sample period from 1999:03:02 to 2018:12:26. The average daily returns vary from 0.0034% (SP500 Financials) to 0.0383%. (Equity REIT). The variance of the daily returns averages from 0.0545 (Bond) to 3.676 (SP500 Financials). Also, the Bond market has the highest reward/risk ratio, whereas the SP500 Financials market has the lowest reward/risk ratio. The distributions of returns in the Equity REIT, SP500, and Bond markets are negatively skewed, while the distribution of Mortgage REIT returns is positively skewed. Each series displays positive kurtosis (leptokurtic), and the Jarque–Bera statistic for each dataset rejects the null hypothesis of normality at the 1% significance level.

Dynamic Conditional Correlations

This study employs the DCC-bivariate GARCH model introduced by Engle (2002) to estimate the time-varying correlations of REIT markets with both the stock and bond markets. In line with Sadorsky (2012), the DCC estimation technique first fits each pair of returns (r_{it}) to the VARMA-GARCH(1,1) model proposed by Ling and McAleer (2003).

Figure 1, Panel A reports the evolution of the dynamic conditional correlations of Equity REIT with Mortgage REIT, Equity REIT with SP500, and Mortgage REIT with SP500. Panel A documents three distinct periods according to the DCC GARCH model.[2] Between 1999:03 and 2007:07, the three dynamic correlations exhibit a positive trend. The linear increase in the strength of the correlations during this period can be attributed to the REITs' inclusion in broad market indices in October 2001. All the stocks in the market

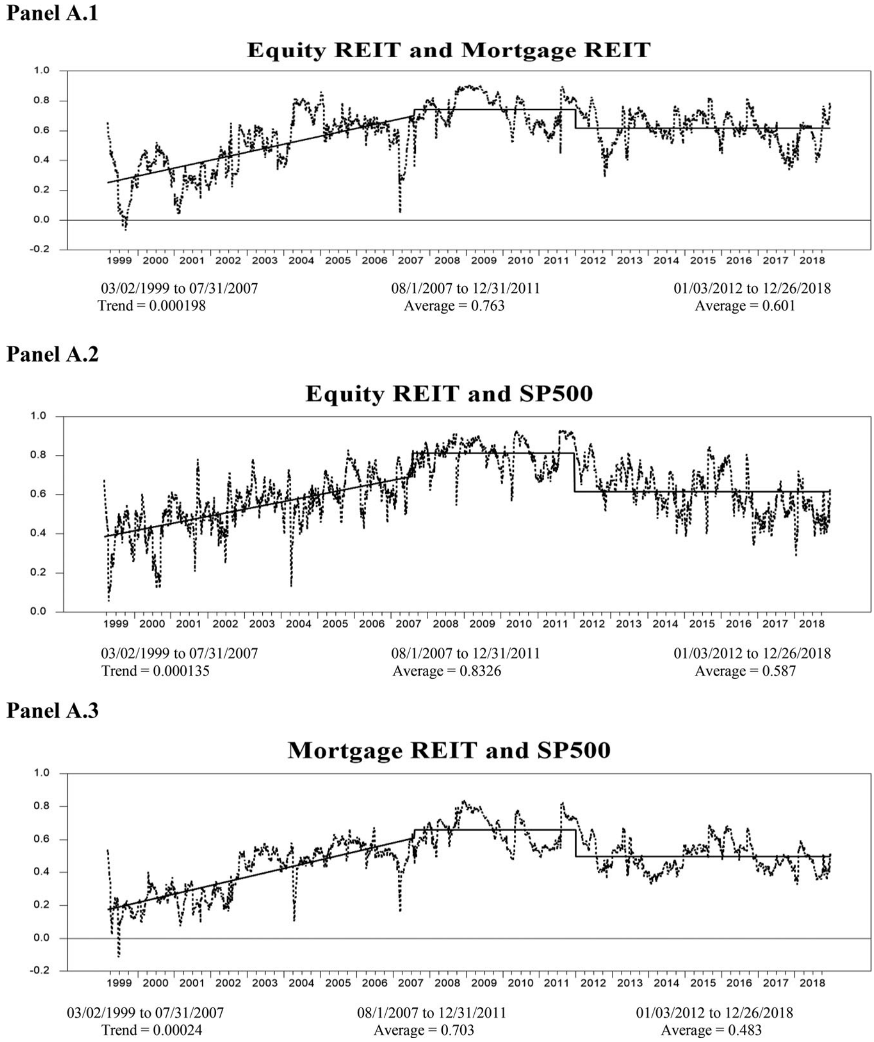
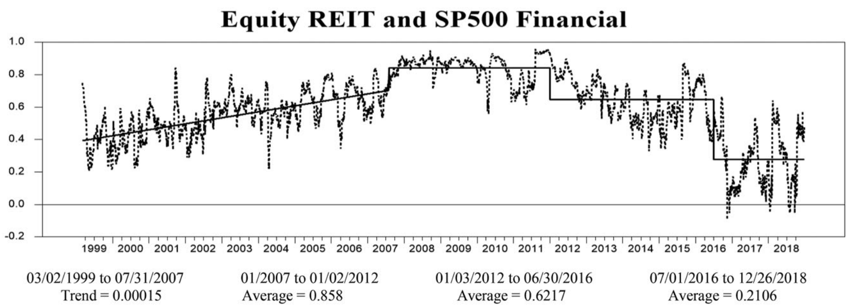


Figure 1. Time-varying conditional dynamic correlations.
Notes: This figure plots the dynamic conditional correlation model (DCC) of the REITs and the SP500, Bond, and Financial SP500 over the sample period from 03/02/1999 to 12/26/2018. The figure also reports the average dynamic correlations for the sub-periods.

indices were subjected to similar trading strategies, a result previously confirmed by Yang et al. (2012).

During the great recession and its early-stage recovery, between 2007:08 and 2011:12, the correlations of Equity REIT with Mortgage REIT (0.76), Equity REIT with SP500 (0.83), and Mortgage REIT with SP500 (0.70) all attained their highest values. As stated by Kawaguchi et al. (2017), the REIT industry relied heavily on debt to finance its operations during the low-interest Greenspan era. This strategy was the driving force behind the observed high correlations from 2008 to 2011. Finally, starting in 2013, the three dynamic correlations drop to a lower stable level: around 0.60 for the correlations of

Panel B.1



Panel B.2

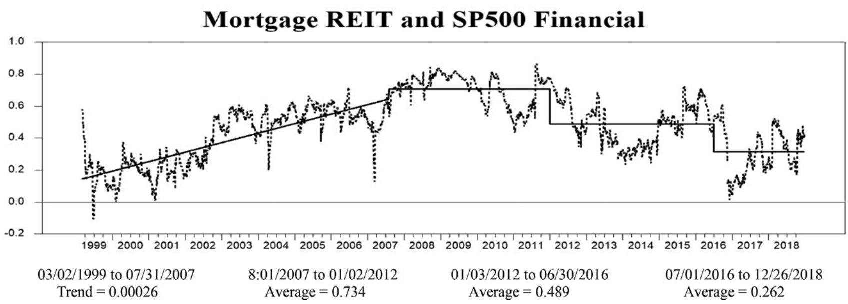


Figure 1. (Continued)

Equity REIT with Mortgage REIT and SP500, and approximately 0.50 for the correlation between Mortgage REIT and SP500.

Panel B reports the dynamic correlations of the SP500 Financials market with the Equity and Mortgage REITs. The two correlations exhibit an evolution similar to those explained in Panel A. Precisely, the correlations show a positive linear trend from 2001 to 2007, followed by a stable high value from 2008 to 2011. They also drop to a lower, stable level during the first four years of the third period, from 2012 to 2016. However, after August 31, 2016, we see a new behavior that was not present in the correlations of Panel A. On this date, equity real estate stocks were removed from the sector of institutional financial firms. As a result of being placed in their own sector, the correlation of Equity REIT with SP500 Financials decreased from 0.62 to 0.24, and the correlation of Mortgage REIT with SP500 Financials decreased less dramatically, from 0.49 to 0.26. The less-dramatic change in the Mortgage REIT correlation was expected as Mortgage REITs did not change GIC sectors. Overall, REIT correlations have decoupled with those in the Financials and suggest that REITs are trading more independently.

Panel C shows the dynamic correlations of Equity and Mortgage REIT markets with the Bond market. During the recessions of 2001 and late 2007, these two correlations are negative due to the high volatility in the different markets and the dominance of the cash flow effect, as documented by Yang et al. (2012). For the two periods from 2004 to 2007 and from 2013 to 2018, the discount rate effect dominated the REITs' correlations with the four markets. Precisely, the correlations were positive: around 0.17 and 0.19 for

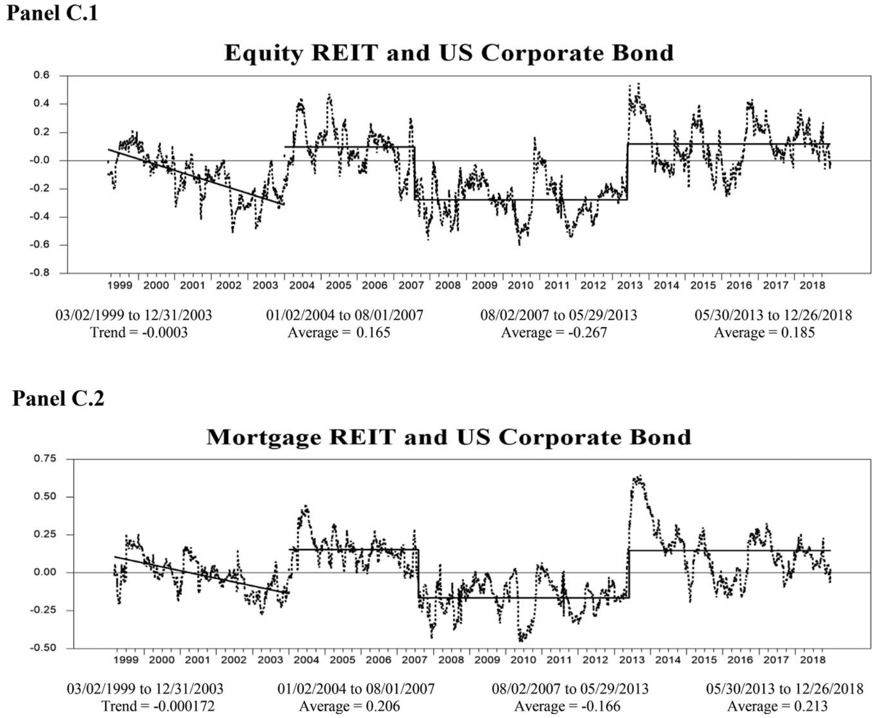


Figure 1. (Continued)

the Equity REIT market vs. the Bond market, and approximately 0.20 and 0.21 for the Mortgage REIT market vs. the Bond market, respectively. Thus, the correlations illustrated in Figure 1 suggest the relation between the REIT markets and the other markets can vary over time due to several factors: REITs' inclusion in or exclusion from broad market indices, the state of the economy, high volatility, and low borrowing rates.

Results

OLS and Dummy Variable Regressions

Our study builds upon the analysis of Yang et al. (2012) by having the same starting date of March 1999 and extending the sample period from June 2008 through December 2018, more than doubling the sample size. We estimate the relation between time-varying correlation and the following macroeconomic variables: Equity REIT and Mortgage REIT (REM,t), Equity REIT and SP500 (RESP500,t), Equity REIT and Bond (REB), Equity REIT and SP500 Financials (REF,t), Mortgage REIT and SP500 (R MSP,t), Mortgage REIT and SP500 (R MSP500,t), or Mortgage REIT and SP500 Financials (R MSP,t) as follows:

$$R_{i,t} = \delta_{1,i} + \delta_{2,i}\ DEF_{t-1} + \delta_{3,i}\ TERM_{t-1} + \delta_{4,i}\ MGTB_{t-1} + \delta_{5,i}\ VIX_{t-1} + \varepsilon_{i,t} \quad (1)$$

We estimate Equation 1 for the different DCCs using OLS and compute the heteroskedasticity and autocorrelation consistent covariance matrix specified by White (1980) and Newey and West (1994). To account for the reported non-normality of the variables in

Table 2. Bai-Perron test for multiple structural break.

R_{MSP}						
R_{EM}						
Sup $F_T(k\|0)$	Observed	BIC	LWZ	Break Point	Lower 95%	Upper 95%
$F_T(1\|0)$	1500***	−4.61	−4.57	03/16/2004	03/11/2004	04/06/2004
$F_T(2\|0)$	831***	−4.66	−4.61	12/15/2009	10/20/2009	12/16/2009
$F_T(3\|0)$	614***	*−4.72*	*−4.64*	02/21/2013	01/07/2013	06/06/2013
$F_T(4\|0)$	462***	−4.72	−4.62			
$F_T(5\|0)$	363***	−4.7	−4.58			
Number of Breaks	3					
R_{ESP}						
Breaks	Observed	BIC	LWZ	Breakpoint	Lower 95%	Upper 95%
$F_T(1\|0)$	591***	−4.5	−4.46	03/17/2003	03/07/2003	04/11/2003
$F_T(2\|0)$	575***	−4.79	−4.73	06/7/2007	05/24/2007	06/14/2007
$F_T(3\|0)$	494***	−4.93	−4.85	06/08/2010	04/16/2010	06/18/2010
$F_T(4\|0)$	425***	*−5.01*	*−4.91*	09/18/2014	05/15/2014	10/20/2014
$F_T(5\|0)$	335***	−4.99	−4.87			
Number of Breaks	4					
R_{EB}						
Breaks	Observed	BIC	LWZ	Breakpoint	Lower 95%	Upper 95%
$F_T(1\|0)$	316***	−3.5	−3.46	04/02/2004	01/8/2004	06/25/2004
$F_T(2\|0)$	529***	−3.94	−3.89	08/29/2007	08/14/2007	09/6/2007
$F_T(3\|0)$	419***	−4.03	−3.95	08/31/2012	08/14/2012	09/5/2012
$F_T(4\|0)$	364***	*−4.11*	*−4.01*	09/04/2015	08/31/2015	11/3/2015
$F_T(5\|0)$	292***	−4.1	−3.98			
Number of Breaks	4					
R_{EF}						
Breaks	Observed	BIC	LWZ	Breakpoint	Lower 95%	Upper 95%
$F_T(1\|0)$	711***	−3.91	−3.87	03/17/2003	03/03/2003	04/07/2003
$F_T(2\|0)$	929***	−4.42	−4.36	09/18/2007	09/10/2007	10/16/2007
$F_T(3\|0)$	746***	−4.54	−4.46	11/22/2010	10/20/2010	11/26/2010
$F_T(4\|0)$	680***	*−4.67*	*−4.57*	09/12/2014	08/04/2014	10/07/2014
$F_T(5\|0)$	522***	−4.63	−4.51			
Number of Breaks	4					
Breaks	Observed	BIC	LWZ	Breakpoint	Lower 95%	Upper 95%
$F_T(1\|0)$	1606***	−5.04	−5	10/07/2002	10/2/2002	10/17/2002
$F_T(2\|0)$	1164***	−5.28	−5.22	10/11/2005	8/11/2005	10/24/2005
$F_T(3\|0)$	963***	−5.43	−5.35	7/16/2009	6/12/2009	7/17/2009
$F_T(4\|0)$	809***	−5.51	−5.41	12/24/2012	9/21/2012	1/10/2013
$F_T(5\|0)$	690***	*−5.55*	*−5.43*	12/ 24/2015	10/23/2015	1/25/2016
Number of Breaks	5					
R_{MB}						
Breaks	Observed	BIC	LWZ	Breakpoint	Lower 95%	Upper 95%
$F_T(1\|0)$	470***	−3.92	−3.88	04/02/2004	03/15/2004	04/22/2004
$F_T(2\|0)$	608***	−4.32	−4.26	08/03/2007	07/26/2007	08/10/2007
$F_T(3\|0)$	514***	−4.45	−4.37	08/17/2012	08/02/2012	08/21/2012
$F_T(4\|0)$	490***	*−4.6*	*−4.5*	08/21/2015	08/18/2015	12/01/2015
$F_T(5\|0)$	342***	−4.5	−4.38			
Number of Breaks	4					
R_{MF}						
Breaks	Observed	BIC	LWZ	Breakpoint	Lower 95%	Upper 95%
$F_T(1\|0)$	803***	−4.19	−4.15	10/7/2002	10/2/2002	10/22/2002
$F_T(2\|0)$	1158***	−4.79	−4.74	05/11/2006	04/28/2006	05/15/2006
$F_T(3\|0)$	931***	−4.92	−4.84	07/22/2009	06/30/2009	07/28/2009
$F_T(4\|0)$	792***	−5.01	−4.91	07/20/2012	06/1/2012	07/25/2012
$F_T(5\|0)$	711***	*−5.09*	*−4.97*	08/11/2015	07/6/2015	08/28/2015
Number of Breaks	5					

Notes. This table reports the sup F(k:0) results, breakpoints with their 95% confidence intervals from Bai-Perron's test for multi-structural breaks in the DCCs for the period from 03/02/1999 to 12/26/2018. The table also reports the selected number of breaks based on the minimum Bayesian Information Criterion (BIC) and the modified Schwarz criterion (LWZ).

Table 3. The sub-sample periods in the DV models.

$D_{i,j}$	j = EM	ESP	EB	EF	MSP	MB	MF
Period i = 1							
From	03/05/1999	03/05/1999	03/05/1999	03/05/1999	03/05/1999	03/05/1999	03/05/1999
To	03/15/2004	03/14/2003	04/01/2004	03/14/2003	10/04/2002	04/01/2004	10/04/2002
i = 2	03/16/2004	03/17/2003	04/02/2004	03/17/2003	10/07/2002	04/02/2004	10/07/2002
	12/14/2009	06/06/2007	08/28/2007	09/17/2007	10/07/2005	08/02/2007	05/10/2006
i = 3	12/15/2009	06/07/2007	08/29/2007	09/18/2007	10/11/2005	08/03/2007	05/11/2006
	02/20/2013	06/07/2010	08/30/2012	11/19/2010	07/15/2009	08/16/2012	07/21/2009
i = 4	02/21/2013	06/08/2010	08/31/2012	11/22/2010	07/16/2009	08/17/2012	07/22/2009
	12/26/2018	09/17/2014	09/03/2015	09/11/2014	12/21/2012	08/20/2015	07/19/2012
i = 5		09/18/2014	09/04/2015	09/12/2014	12/24/2012	08/21/2015	07/20/2012
		12/26/2018	12/26/2018	12/26/2018	12/23/2015	12/26/2018	08/10/2015
i = 6					12/24/2015		08/11/2015
					12/26/2018		12/26/2018
The number of Dummy variables (m_j)	4	5	5	5	6	4	5

Notes. This table describes the periods when the dummy variables ($D_{i,j}$) in the DV models take the value of one. EM refers to the DCC of the Equity REIT and the Mortgage REIT; ESP refers to the DCC of the Equity REIT and SP500; EB refers to DCC of the Equity REIT and Bond, EF refers to the DCC of the Equity REIT and SP500 Financials, MSP refers to the DCC of the Mortgage REIT and SP500, MB refers to the DCC of the Mortgage REIT and Bond. MF refers to the DCC of the Mortgage REIT and SP500 Financials. For example, $D_{1,EM}$ is the dummy variable that takes the value of one in the first subsample (03/05/1999-03/15/2004) in the EM equation.

Equation 1 and the lack of knowledge about the underlying data-generating process, we bootstrap to construct the 99%, 95%, and 90% confidence interval for the parameters. First, we draw 10,000 samples of 4,951 observations for each variable with replacement and estimate the regression for each sample. Next, we follow Cameron and Trivedi's technique (2005) to compute the *t*-statistics in each regression. To further explore potential structural and coefficient instability in the relation between DCCs and their selected determinants, we employ the recursive version of Bai-Perron's (Bai & Perron, 1998, 2003) tests which determines the structural breaks even though the exact break dates are unknown.[3]

Table 2 reports the sup F(k;0) statistics of no breaks against k breaks' alternative. We set the maximum number of breaks (k) to 5, the trimming value at 0.15 (i.e., each regime contains at least 15% of the observations), and the breaking parameter to 5. We selected the number of breaks by repeatedly testing the null of no breaks against k breaks' alternative, increasing k until the null cannot be rejected or until the maximum number of permitted breaks is reached. Among all cases where the null is rejected (each case with a different total number of breaks), we select the one associated with the minimum Bayesian information criterion (BIC) and modified Schwarz criterion (LWZ), as proposed by Yao (1988) and Liu et al. (1997), respectively. All F(K|0) tests are statistically significant at the 1% level. However, the BIC and the LWZ statistics select three breaks for R_{EM}, four breaks for R_{ESP}, R_{EB}, and $R_{MF,}$ and five breaks for R_{MSP} and R_{MF}. The 95% confidence interval for the 29 breaks in the seven DCCs equations average 38 days. In sum, the analysis confirms the time-varying nature and the structural instability of the correlations between the REITs and the other financial markets.

Next, we utilize the dummy variable regression (DV) to allow the intercept and the estimated coefficients of the four determinants to assume different values during each of the structurally distinct sub-periods identified by Bai-Perron tests.

Table 4. OLS results from regressing the conditional correlations on the macroeconomic variables.

	R_{EM}	R_{ESP}	R_{EB}	R_{EF}	R_{MSP}	R_{MB}	R_{MF}
R^2 adjusted	0.262	0.290	0.239	0.247	0.348	0.209	0.327
Constant	0.420***	0.452***	0.234***	0.329***	0.318***	0.234***	0.222***
DEF_{t-1}	0.242***	0.182***	−0.059***	0.195***	0.269***	−0.108***	0.306***
$Term_{t-1}$	0.039***	0.029***	−0.027***	0.027***	0.019***	−0.001***	0.020***
$MGTB_{t-1}$	−0.006***	−0.017***	0.006***	−0.005***	−0.007***	0.006***	0.002
VIX_{t-1}	−0.008***	−0.003***	−0.009***	0.001**	−0.007***	−0.006***	−0.005***
σ	0.157***	0.132***	0.198***	0.183***	0.129***	0.170***	0.164***
White Test							
χ^2 Statistics	970***	895***	1116***	629***	1528***	804***	1060***
LQ-Statistics							
Lags 2	9476***	9348***	9579***	9571***	9459***	9628***	9602***
Lags 4	18437***	17966***	18745***	18695***	18378***	18901***	18813***
Lags 6	26957***	25864***	27508***	27370***	26807***	27821***	27654***

Note. This table reports OLS results from regressing the seven dynamic conditional correlations on the first lag of the DEF, Term, MGTB, and VIX for the period from 03/2/1999 to 12/26/2018. The table also reports the χ^2 statistics for the heteroscedasticity White test and serial correlation with the L.Q. Tests at the 2, 4, and 6 lags.
*, **, *** denote significance levels at 10%, 5% and 1% determined by the bootstrapped t* and confidence intervals.

$$R_{j,t} = \sum_{i=1}^{m_j}[\alpha_{i,j}\ (D_{i,j}) + \ \beta_{i,j}\ (D_{i,j}\ DEF_{t-1})\ + \gamma_{i,j}\ (D_{i,j}\ TERM_{t-1}) + \ + \ \delta_{i,j}\ (D_{i,j}\ MGTB_{t-1}) + \theta_{i,j}\ (D_{i,j}\ VIX_{t-1})] + \ \varepsilon_{j,t}, \tag{2}$$

where j = {EM, ESP, EB, EF, MSP, MB, MF}, and m_j is the number of dummy variables in the j equation. Table 3 describes the design of each dummy variable, which accounts for the specified breaks from Bai–Perron tests.

Tables 4 and 5 report the results of estimating regressions for the different DV specifications. Their restricted version is estimated using OLS with a consistent covariance matrix that allows for heteroskedasticity and serial correlation. The tables report the statistical significance of the estimated coefficient determined by bootstrapping and show confidence intervals for each sub-sample in the data. The residuals from the restricted and unrestricted equations exhibit severe heteroskedasticity and serial correlation, as illustrated by the White and Ljung–Box Q tests. We also account for the two classical assumptions violations by calculating the heteroskedasticity and autocorrelation consistent covariance matrix.

The null hypothesis that DCCs respond symmetrically to their selected determinants in all the sub-periods is rejected at the 1% level. Allowing the four determinates' intercepts and coefficients to vary across different structural periods more than doubles the adjusted-R^2 of each model. For example, the average adjusted-R^2 of the restricted and unrestricted equations are 27% and 77%, meaning the unrestricted equations are a better fit for the data.

Continuing, the estimated coefficients in the unrestricted equations diverge from their counterparts in the restricted equations in magnitude, sign, and statistical significance. For example, in the restricted equations, we see a positive relation between DEF and R_{EM}, R_{ESP}, and R_{MSP}. Yang et al. (2012) attribute this positive relation to the leverage and risk premium. The estimates from the unrestricted equations confirm a positive relation between DEF and the dynamic correlations in all the sub-periods. However, the DEF

Table 5. Dummy variable OLS results from regressing the conditional correlations on the macroeconomic variables.

	R_{EM}	R_{ESP}	R_{EB}	R_{EF}	R_{MSP}	R_{MB}	R_{MF}
R^2 Adjusted	0.741	0.737	0.697	0.788	0.853	0.710	0.849
$D_{1,j}$	0.330***	0.133***	0.326***	0.185***	0.070***	0.190***	0.033
$D_{1,j}$ DEF_{t-1}	0.034	0.055***	−0.122***	0.028	0.146***	−0.178***	0.107***
$D_{1,j}$ $Term_{t-1}$	−0.030***	0.018***	−0.004	−0.004	−0.024***	0.018***	−0.006**
$D_{1,j}$ $MGTB_{t-1}$	0.045***	−0.003	−0.025***	0.010***	0.005***	−0.018***	0.009***
$D_{1,j}$ VIX_{t-1}	−0.001*	0.010***	−0.010***	0.010***	0.003***	−0.001	0.003***
$D_{2,j}$	0.518***	0.409***	0.376***	0.410***	0.396***	0.071**	0.483***
$D_{2,j}$ DEF_{t-1}	0.049***	0.056**	−0.275***	0.062***	0.190***	0.047	0.119***
$D_{2,j}$ $Term_{t-1}$	0.058***	−0.084***	0.067***	−0.079***	−0.053***	0.089***	−0.033***
$D_{2,j}$ $MGTB_{t-1}$	0.003***	0.023***	−0.003	0.022***	0.029	−0.014***	0.016***
$D_{2,j}$ VIX_{t-1}	0.001***	0.014***	−0.006***	0.014***	−0.004***	0.000	−0.004***
$D_{3,j}$	0.024	0.728***	−0.467***	0.869***	0.471***	−0.303***	0.546***
$D_{3,j}$ DEF_{t-1}	0.268***	0.052***	0.092***	0.021***	0.055***	0.061***	−0.016***
$D_{3,j}$ $Term_{t-1}$	0.049***	0.009***	0.053***	−0.008***	0.058***	0.048***	0.083***
$D_{3,j}$ $MGTB_{t-1}$	0.295	−0.152	−0.048	−0.080**	0.009***	0.025	0.071
$D_{3,j}$ VIX_{t-1}	0.010***	−0.001***	−0.003***	−0.001**	0.000	−0.003***	0.002*
$D_{4,j}$	0.321***	0.385***	−1.058***	0.610***	0.159***	−0.939***	0.212***
$D_{4,j}$ DEF_{t-1}	0.072**	0.107***	0.307***	−0.008***	0.104***	0.027***	0.212***
$D_{4,j}$ $Term_{t-1}$	0.057***	0.015	0.402***	−0.058***	0.024***	0.475***	0.007
$D_{4,j}$ $MGTB_{t-1}$	0.291	0.129	1.336*	0.085	0.259	0.825	0.267
$D_{4,j}$ VIX_{t-1}	0.009***	0.011***	−0.003	0.014***	0.012***	0.002	0.009***
$D_{5,j}$		0.253***	0.301***	−0.419***	0.426***	0.209***	0.505***
$D_{5,j}$ DEF_{t-1}		0.231***	−0.472***	0.469***	0.237***	−0.441***	0.171***
$D_{5,j}$ $Term_{t-1}$		0.027***	0.096***	0.105***	−0.071***	0.111***	−0.096***
$D_{5,j}$ $MGTB_{t-1}$		0.002	−0.242	−0.028	0.110	0.379	0.247
$D_{5,j}$ VIX_{t-1}		0.004***	0.006***	0.016***	0.001	0.007***	−0.001***
$D_{6,j}$					0.220***		−0.086***
$D_{6,j}$ DEF_{t-1}					0.165***		0.479***
$D_{6,j}$ $Term_{t-1}$					0.059***		−0.062***
$D_{6,j}$ $MGTB_{t-1}$					−0.020		−0.195
$D_{6,j}$ VIX_{t-1}					0.003***		0.008***
σ	0.093	0.080	0.129	0.096	0.061	0.103	0.078
F Statistics	609***	421***	332***	632***	678***	436***	687***
White Test							
χ^2 Statistics	1211***	1164***	1116***	2683***	1059***	3306***	1666***
LQ-Statistics							
Lags 2	8842***	8230***	8599***	8083***	8239***	8498***	8408***
Lags 4	16545***	14728***	15731***	14667***	14874***	16126***	15582***
Lags 6	23281***	19758***	21539***	19965***	20147***	22947***	21656***

Note. This table reports DV results from regressing the seven dynamic conditional correlations on the first lag of the DEF, Term, MGTB, and VIX, where both the slope and constant terms are allowed to change at each sub-period from 03/2/1999 to 12/26/2018. The table reports the χ^2 statistics of the White test for heteroscedasticity and the L.Q. Tests for serial correlation at the 2, 4, and 6 lags. The table also reports the F-statistics for testing the null hypothesis that DCCs respond symmetrically to their selected determinants in regime one and two.

*, **, *** denote significance levels at 10%, 5% and 1% determined by the bootstrapped t* and confidence intervals.

coefficient's average magnitude in the restricted equations (0.231) dramatically exceeds that calculated in the unrestricted equations (0.121). Moreover, the magnitude of the DEF coefficient varies across the different sub-periods. For example, $\beta_{1,EM}$, $\beta_{2,EM}$, $\beta_{3,EM}$, *and* $\beta_{4,EM}$ are .034, .049, .268, and .072, respectively. Also, the signs of the DEF coefficients in the restricted equations for R_{EB} and R_{MB} are negative. In contrast, the corresponding estimates from the unrestricted equations show that the relation is positive or statistically insignificant ($\beta_{3,EB}$, $\beta_{4,EB}$, $\beta_{3,MB}$, and $\beta_{4,MB}$), whereas estimates for most of the remaining sub-periods are negative and statistically significant ($\beta_{1,EB}$, $\beta_{2,EB}$, $\beta_{5,EB}$, $\beta_{1,MB}$, *and* $\beta_{5,MB}$).

The estimated coefficients on VIX produce some interesting insights. The signs of the VIX coefficients in the restricted equations indicate an adverse effect of the VIX on most of the different DCCs. In this case, the unrestricted estimates provide a better understanding of how the relation has changed over time. The unrestricted estimates in the later periods exhibit a positive and statistically significant relation between VIX and most DCCs. For example, $\theta_{4,\,EM}, \theta_{4,\,ESP}, \theta_{4,\,EF}, \theta_{4,\,MSP}, \theta_{4,\,MF}, \theta_{5,\,ESP}, \theta_{5,\,EB}, \theta_{5,\,EF}, \theta_{5,\,M.B.},$ and $\theta_{6,\,MF}$ are all estimated to be positive and statistically significant, whereas the remaining coefficients in these periods are statistically non-significant. The later periods capture the positive association between the lower correlations and the lower volatility after the Great Recession, as illustrated by the negative and statistically significant $\theta_{3,\,E.B.}$ and $\theta_{3,\,E.F}$. The correlation between REITs and the Bond market were weaker during the financial crisis. However, the higher volatility during the Great Recession was associated with a weaker correlation between REITs and the Bond market, as illustrated by the negative and statistically significant $\theta_{3,\ EB}$ and $\theta_{3,\ EF}$. In sum, the restricted equations present the constant impact of macroeconomic driving forces on the DCCs. Ignoring the sub-sample instability and structural changes documented in our study will cause the restricted equations to be incorrectly specified and their estimates to be biased.

Markov Switching Model

Recall that the dummy variables are defined according to changes (breaks) in the composition of broad market indices, state of the economy, volatility, and borrowing rates. DV model performance depends strongly on the structural breaks' prior specification, so the metrics previously detailed overestimate the model's performance. To account for the absence of previous knowledge of the structural breaks, we utilize a constant-variance, first-order, Markov regime-switching model (MRS). The MRS's main advantage is its ability to identify the regime's shift without any prior specification. Also, the MRS could prove useful during early periods of structural changes.

An extensive literature has employed MRS techniques to examine the time-varying relation in real estate, finance, and economics.[4] This model's main advantage is that the switching mechanism, an unobservable state variable that follows a first-order Markov chain, is wholly independent of any selected dates. The variance is constant within each regime, but the different regimes allow the estimated coefficients to exhibit time dependence. This characteristic of the MRS model is of great import, given the high volatility we experience in the REIT market as it becomes more integrated with the stock market. Also, the introduction of leveraged and inverse ETFs in the REIT market has impacted their underlying REIT stock price volatility, as documented by Hardin et al. (2020) and Boney-Dutra et al. (2013).

Our model is controlled by a two-state Markov chain process permitting the estimated coefficients and variances to change through discrete jumps rather than a continuous process. The regime-shifting model parameters are calculated using the EM algorithm proposed by Dempster et al. (1977) and Hamilton (1989). This approach further accounts for the non-normality of the REIT indices by utilizing a mixture-of-normals approach as discussed in Ammann and Verhofen (2006). Specifically, our model is informed by a two-state Markov chain process indexed by S_t, which assumes the value 1 or 2 depending on the variance (high or low) of the REIT index. Thus, we base our empirical description of DCCs on the following mixture of two conditionally normal distributions:

$$R_t|\varphi_{t-1} \sim \begin{bmatrix} N(a_{1,0} + a_{1,1}DEF_{t-1} + a_{1,2}TERM_{t-1} + a_{1,3}MGTB_{t-1} + a_{1,4}VIX_{t-1},\ b_1),\ w.p.\ \ p_{1t} \\ N(a_{2,0} + a_{2,1}DEF_{t-1} + a_{2,2}TERM_{t-1} + a_{2,3}MGTB_{t-1} + a_{2,4}VIX_{t-1},\ b_1)\ w.p.\ \ 1 - p_{1t} \end{bmatrix}, \tag{3}$$

where p_{1t} is the probability of being in the (unobserved) regime (state 1) at time t, specified as follows:

$$p_{1t} = (1 - Q)\quad Pr[S_{t-1} = 2|\varphi_{t-1}] + (P)\quad Pr[S_{t-1} = 1|\varphi_{t-1}] \tag{4}$$

S_{t-1} denotes the unobservable regime at time "$t - 1$" based on ϕ_{t-1}, the available information at time t-1. In addition, the formation of regime S_t depends on the outcome of a temporally homogenous, first-order Markov chain with state space {1, 2} and the following constant matrix of transition probabilities:

$$\begin{aligned} P_{11} &= Pr[S_t = 1|\ S_{t-1} = 1] \\ P_{21} &= Pr[S_t = 2|\ S_{t-1} = 1] \\ P_{22} &= Pr[S_t = 2|\ S_{t-1} = 2] \\ P_{12} &= Pr[S_t = 1|\ S_{t-1} = 2], \end{aligned} \tag{5}$$

where P_{21} is the probability of moving from state 1 to state 2, and P_{12} is the probability of moving from state 2 to state 1. Intuitively, P_{11} and P_{22} indicate the probabilities that the current state of the regime will be the same as the previous state. This model permits the estimated coefficients and variances to change through discrete jumps rather than a continuous process. The parameters of the regime-shifting model are calculated using the EM algorithm proposed by Dempster et al. (1977) and Hamilton (1989). In addition, this approach accounts for the non-normality of the REIT indices by utilizing a mixture-of-normals approach. For more details, see Ammann and Verhofen (2006).

Following Hamilton (1989), we estimate the expected durations of states 1 and 2:

$$\begin{aligned} Dur_1 &= \frac{1}{1 - P_{11}} \\ Dur_2 &= \frac{1}{P_{12}} \end{aligned} \tag{6}$$

Intuitively, these values represent the number of periods a regime is expected to last once it has been established. We also calculate the long-run average probabilities for the Markov chain (Ergodic probabilities for states 1 and 2) as follows:

$$\begin{aligned} \Pr(S_t = 1) = \pi_1 &= \frac{1 - P_{22}}{2 - P_{11} - P_{22}},\ \text{and} \\ \Pr(S_t = 2) = \pi_2 &= \frac{1 - P_{11}}{2 - P_{11} - P_{22}} \end{aligned} \tag{7}$$

Based on the ergodic probabilities, we calculate the weighted values (long-term) of the estimated coefficients on the selected macroeconomics determinants as follows:

$$a_{LR,j} = \pi_1(a_{1,j}) + \pi_2(a_{1,j}),\ where\ j = 0,\ \ldots,\ 4 \tag{8}$$

We also examine the relevance of the state-dependent model by calculating the regime classification measure (RCM) statistics introduced by Ang and Bekaert (2002):

$$RCM = 400\ x\ \frac{1}{T}\sum_{t=1}^{T} \Pr[S_t = 1|\varphi_t](1 - \Pr[S_t = 1|\varphi_t]), \tag{9}$$

Table 6. Markov-switching results from regressing the conditional correlations on the macroeconomic variables.

	R_{EM}	R_{ESP}	R_{EB}	R_{EF}	R_{MSP}	R_{MB}	R_{MF}
R^2 adjusted	0.770	0.472	0.779	0.692	0.406	0.416	0.649
Constant							
$a_{1,0}$	0.513***	0.495***	0.381***	0.405***	0.442***	0.555***	0.161***
$a_{2,0}$	0.428***	0.213***	0.328***	−0.318***	0.009	0.180***	0.179***
$a_{LR,0}$	0.482	0.353	0.356	0.104	0.234	0.381	0.168
DEF_{t-1}							
$a_{1,1}$	0.042***	0.077***	−0.397***	0.128***	0.128***	−0.414***	0.605***
$a_{2,1}$	0.083***	0.474***	−0.132***	0.800**	0.399**	−0.081***	−0.002
$a_{LR,1}$	0.057	0.278	−0.275	0.408	0.258	−0.260	0.354
$Term_{t-1}$							
$a_{1,2}$	0.019***	0.055***	−0.041***	0.070***	−0.021***	−0.009***	0.015***
$a_{2,2}$	0.009***	−0.026***	−0.006*	−0.194***	0.045***	0.037***	0.027***
$a_{LR,2}$	0.015	0.014	−0.025	−0.040	0.011	0.012	0.020
$MGTB_{t-1}$							
$a_{1,3}$	0.014***	−0.030***	0.017***	−0.023***	0.001**	0.019***	0.021***
$a_{2,3}$	0.022***	−0.004***	0.003**	0.032***	−0.047***	−0.010***	−0.035***
$a_{LR,3}$	0.017	−0.017	0.010	−0.0001	−0.022	0.005	−0.002
VIX_{t-1}							
$a_{1,4}$	0.005***	0.0004***	−0.006***	−0.001***	0.001***	−0.009***	−0.018***
$a_{2,4}$	−0.007***	−0.001***	−0.004***	0.018***	−0.002***	−0.005***	0.014***
$a_{LR,4}$	0.0004	−0.001	−0.005	0.007	−0.0001	−0.007	−0.005
σ_1	0.004***	0.003***	0.008***	0.011***	0.002***	0.003***	0.005***
σ_2	0.016***	0.023***	0.017***	0.019***	0.019***	0.043***	0.029***
P_{11}	0.995***	0.985**	0.992**	0.993**	0.990**	0.983**	0.987***
P_{12}	0.008**	0.015***	0.010**	0.010**	0.011***	0.020***	0.019***
White Test							
χ^2 Statistics	318***	512***	190***	239***	616***	385***	133***
LQ-Statistics							
Lags 2	8816***	9175***	8523***	8726***	9388***	9469***	8807***
Lags 4	16297***	17413***	16163***	16179***	17897***	18323***	16377***
Lags 6	22650***	24775***	22963***	22619***	25489***	26559***	22900***
Dur_1	216	65	123	137	99	59	75
Dur_2	121	67	104	98	92	51	52
Ergodic Probability							
π_1	0.640	0.494	0.540	0.584	0.519	0.536	0.587
π_2	0.360	0.506	0.460	0.416	0.481	0.464	0.413
RCM	2.322	7.527	3.847	7.750	6.287	7.668	7.180
F-stat							
H_0: $a_{1,i} = a_{2,i}$	1926***	221***	2304***	823***	539***	420***	464***
$\uparrow^2$-stat							
H_0: $\sigma_1 = \sigma_2$	438***	795***	225***	212***	1085***	716***	504***

Note. This table reports MRS results from regressing the seven dynamic conditional correlations on the first lag of the DEF, Term, MGTB, and VIX, where both the slope and constant terms are allowed to change in low-variance (regime 1) and high-variance (regime 2) periods for the period from 03/2/1999 to 12/26/2018. Table 6 reports the χ^2 statistics of the White test for heteroscedasticity and the L.Q. Tests for serial correlation at the 2, 4, and 6 lags. The table also reports the duration of the low-variance regime (Dur1), the duration of the high-variance regime (Dur2), Ergodic probabilities of the two regimes, RCM test, both the F-statistics and χ^2 statistics for testing null the coefficients and the variances are not statistically different in the two regimes.

where $[S_t = j|\varphi_t]$ are the smoothed probabilities conditioned on the available information set φ_t, and $0 \leq RCM \leq 100$. As stated by Ang and Bekaert (2002), "the ex-post probability of observing one of the regimes should be close to 1 at all times when regime classification is perfect." Thus, an RCM value of 0 will perfectly support a multi-regime Markov model, whereas a value of 100 will favor a single-regime model. We also test whether the estimated coefficients (variance) in the two regimes are statistically different.

Table 7. In-sample forecasting evaluations.

	R_{EM}	R_{ESP}	R_{EB}	R_{EF}	R_{MSP}	R_{MB}	R_{MF}	Average
R^2								
OLS	0.262	0.29	0.239	0.247	0.348	0.209	0.327	0.275
MRS	0.77	0.472	0.779	0.692	0.406	0.416	0.649	0.598
DV	0.741	0.737	0.676	0.788	0.853	0.710	0.849	0.765
Log-Likelihood								
OLS	2147	3007	999	1364	3118	1747	1920	2043
MRS	5435	4563	3889	3470	5760	3831	4111	4437
DV	4743	5475	3112	4512	6811	4271	5636	4937
AIC								
OLS	−0.865	−1.213	−0.401	−0.549	−1.258	−0.704	−0.773	−0.823
MRS	−2.191	−1.838	−1.566	−1.396	−2.322	−1.542	−1.656	−1.787
DV	−1.909	−2.203	−1.248	−1.813	−2.74	−1.716	−2.266	−1.985
SBC								
OLS	−0.857	−1.205	−0.393	−0.541	−1.25	−0.696	−0.765	−0.815
MRS	−2.172	−1.82	−1.548	−1.378	−2.304	−1.524	−1.637	−1.769
DV	−1.881	−2.168	−1.213	−1.779	−2.7	−1.682	−2.225	−1.950

Note. This table reports R^2 from regressing DCCs on the in-sample forecast. The table also reports the Log-Likelihood, AIC, and SBC for the OLS, DV, and MRS regressions from 03/2/1999 to 12/26/2018.

We next employ R^2 from regressing the DCCs on their fitted values, log-likelihood, Akaike information criterion (AIC), and Schwarz Bayesian criterion (SBC) to compare the performance of the MRS, the OLS model with dummy variables (henceforth DV), and the simple OLS regression model (henceforth OLS). All four statistics test the fundamental hypothesis that DCCs respond differently to their determinants, depending on the identified breaks (OLS with dummy variables) or whether the economy is operating in regime 1 or regime 2 (Markov).[5]

Table 6 reports the estimated parameters from the MRS model. The results provide strong evidence for two distinct regimes of behavior in all DCCs. First, the average standard deviation of Regime 1 (low-variance) is 0.005, whereas the average standard deviation of Regime 2 (high-variance) is 0.024. The χ^2-statistics reject the null that $\sigma_1 = \sigma_2$ at the 1% significance level in all the DCCs determined under Markov switching models.

Within the low-variance regime, the estimated coefficients are larger (smaller) than those of the high-variance regime in 37% (6%), and many times the estimated coefficients have a different sign. The low-variance regime has a longer expected duration (111 days) than the high-variance regime (84 days), and the average ergodic probability of the low-variance regime (.56) is higher than that of the high-variance regime (.44). Thus, empirically we observe that the low-variance regime is more persistent. Also, the average regime classification (RCM) is 6, confirming the reliable regime classification revealed by the high ex-post probability of observing one of the regimes at all times.

We evaluate the in-sample forecasting results of the OLS, DV, and MRS regressions by comparing their R^2, log-likelihood, AIC, and SBC. Table 7 confirms the time-varying relation between DCCs and their four determinants, as captured by the DV and MRS regressions' superior performance. For example, the R^2 values obtained by regressing the actual observations of the DCCs onto their in-sample forecasts are 0.275, 0.765, and 0.598 under the OLS, DV, and MRS models, respectively. Similarly, the average log-likelihood of OLS is 2043, but 4937 and 4437 for the DV and MRS models, respectively. Also, AIC and SBC decreased from −0.818 in the OLS regression to −1.9727 in the DV and MRS regressions. Thus, the DV and MRS regressions confirm that restricted equations with constant impacts are incorrectly specified and generate biased estimates over an extended historical dataset.

Conclusions

The analysis of dynamic relationships between REIT markets and financial markets plays a central role in real estate portfolio allocations. This study investigates the time-varying nature of correlations between equity and mortgage REIT markets and the equity (SP500) and bond markets. Our study documents six structural shifts (sub-periods characterized by different dynamic correlations) generated by the state of the economy, levels of leverage, the inclusion or exclusion of REITs from the major S&P indices, and the new GIC sector. The time-varying correlations can be explained by the small set of macroeconomic variables introduced by Yang et al. (2012): default spread, term spread, mortgage spread, and the VIX. Further, we extend their sample period to 2018 and allow the estimated intercepts and coefficients of these explanatory variables to vary across the sub-periods when the dynamic correlations exhibit a structural shift. Our model modifications significantly improve the equations' overall fit as measured by the adjusted-R2, whose average value (across models) increases from 37% to 78%.

The results have practical implications for portfolio and risk management. For example, on August 31, 2016, the REIT market experienced a significant structural change: The MSCI moved real estate companies and REITs from the financial sector to their own sector, the 11th GICS sector. This movement created the first new sector added since the GICS was designed in 1999. We show that the correlation between Equity REITs and Financials dropped markedly following this change. As such, REITs started trading more independently. As such, optimal weights and usage of REITs in optimal portfolios have changed.

In conclusion, REITs' continuous and dramatic changes with the rest of the market might pose new challenges to the current and future role that REITs play in a mixed-asset portfolio, how REITs correlate to private markets, and how REITs now perform under extreme market conditions.

Notes

1. Graphs of each data series are available from the authors upon request.
2. A table of the DCC-GARCH results are available from the authors upon request but have been omitted here for the sake of brevity. The results confirm the strong persistence of the dynamic conditional correlations between the Equity REIT, Mortgage REIT, Bond, SP500, and SP500 Financials markets. Moreover, the long-run persistence of the conditional correlations is stronger than the short-term persistence.
3. In other models, we use the predetermined breaks identified in Yang et al. (2012). The results are qualitatively similar and are available from the authors upon request.
4. See, for example, Beracha et al. (2019), Freybote and Seagraves (2018), Liow and Ye (2017), Evans and Mueller (2016), Tsolacos et al. (2014), and Anderson et al. (2012).
5. A graph that plots the smoothed probabilities of the DCCs being in the low-variance regime conditioned on the available information at time *t*-1 is available from the authors upon request.

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