REITs’ dynamics under structural change with unknown break points ★

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Abstract

This paper considers dynamic behaviors of returns on real estate, equity markets, and related macroeconomic variables. Using monthly data measured over the period 1971–2004, we find a single structural break in a multivariate time series model of returns on REITs, returns on equities, industrial production, aggregate price inflation, default risk, the term spread, and short term interest rates. The break date is October 1980. A distinct difference in the contemporaneous causal structure generating these variables before and after the break is found. The paper shows that REITs play a more important role in the US economy after the 1980 break than before.

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1. Introduction

Real Estate Investment Trusts (REITs) have played an important role in US real estate investment since their creation by Congress in the 1960s. REITs have supported the indi-
rect investment or finance of the real estate sector with Mortgage-backed Securities (MBS).\(^1\) They have become an important alternative investment tool for a wealth-building portfolio, compared to more traditional stock market investments. According to the National Association of Real Estate Investment Trusts (NAREIT), there are approximately 200 publicly traded REITs in the US today. Shares of these companies are traded on major stock exchanges, which set them apart from traditional real estate companies. The ratio of market capitalization in REITs to that in the S&P 500 was greater than 19% in 2003, compared to less than 10% in 1983.\(^2\) As the market size of REITs increases, the positive relationship between returns on REITs and stock appears to be weakening. For example during the first three years of the 2000s, an inverse relationship existed between returns on REITs and returns on the S&P 500. REITs jumped 63% in value from the end of 1999 to the beginning of 2004, compared to a 23% drop in the S&P 500 index during the same period. The relationship between REITs, equity returns and other related variables will be investigated in this paper.

Several authors have studied the dynamics of the interface between financial markets and macroeconomic variables. Chen et al. (1986) find the relationship between financial markets and the macroeconomy is not unidirectional. McCue and Kling (1994) found that a shock to nominal interest rates has a significant negative effect on real estate returns using a vector autoregression (VAR) model fit over the period 1971–1991. However, they found shocks to other macroeconomic variables (output and investment) have little explanatory power on movements in real estate returns. Ewing and Payne (2005) studied the magnitude and persistence of unanticipated changes in four macroeconomic variables (monetary policy, real output, default risk premium, and inflation) on REITs returns using a generalized impulse response functions from a VAR (Koop et al., 1996, and Pesaran and Shin, 1998). Payne (2003) extends the Ewing and Payne (2005) model using three classifications of REITs: equity, mortgage, and hybrid types of REITs. The three types of REITs respond in a similar manner to shocks in macroeconomic variables, with the exception of inflation and default risk.

Gyourko and Keim (1992) demonstrate that the return on REITs is affected by the return of S&P 500 investments using a regression model. Peterson and Hsieh (1997) also find that equity REITs are significantly related to stock portfolios in terms of risk premiums and return rates using the five-factor model of Fama and French (1993). Okunev et al. (2000) support these studies by finding a unidirectional (Granger-type) causal relationship from stock market returns to real estate returns.

These studies use time series data. Several have been carried out assuming there has been no structural change. Others have considered the possibility of structural break(s) at an a priori known break point (Ewing and Payne, 2005, Payne, 2003, Chui et al., 2003, Okunev et al., 2000). Such breaks have not been found using tests for an unknown

\(^1\) For details on REITs and their regulations see National Association of Real Estate Investment Trusts (2004). Briefly, a company which qualifies as a REIT is permitted to deduct dividends paid to its shareholders from its corporate taxable income. REITs are legally required to distribute at least 90\% of their taxable income to shareholders annually in the form of dividends, thus differentiating REITs from other stock assets. Additionally, no more than 50\% of the shares can be held by five or fewer individuals during the last half of each taxable year. Further, at least 75\% of the total investment assets must be in real estate related entities.

\(^2\) For the S&P 500, the market capitalization value is based on year end total indexed assets (Standard & Poors, “Annual Survey of S&P Indexed Asset”, 2003). And for REITs, it is equity market capitalization outstanding (National Association of Real Estate Investment Trusts (2004) American Annual market capitalization).
break point. It is of general interest to know if the empirical relationship between REITs and other related variables has changed and where in the data that change first appears.

In addition to questions on break points, the previous literature has assumed an a priori structural ordering on contemporaneous covariance on innovations from each of the variables studied. Ewing and Payne (2005) and Payne (2003) use predetermined contemporaneous causations, a generalized impulse response analysis, to study the dynamics of REITs including other macroeconomic variables. Recent contributions in computer science and econometrics have focused on the use of Directed Acyclic Graphs (DAGs) and algorithms of inductive causation to provide empirical evidence on contemporaneous orderings on innovations form a vector autoregression (Swanson and Granger, 1997 and Bessler and Akleman, 1998). These innovations in modeling allow the data to a have a stronger influence on how one models contemporaneous relationships than have been heretofore permitted.

The objective of this paper is to build an empirical model, in the likeness of that of Chen et al. (1986), to cast further light on the relationships among returns on REITs, equities, and other macroeconomic variables. A structural break test (the Sup LM test, proposed originally by Andrews, 1993) is applied, where possible break dates are not imposed a priori. We find a break at October 1980. Given this break date, two separate VARs are estimated, one for each sub-period. GES algorithm for inductive causation is used to identify structural causal flows among contemporaneous innovations on each sub-period VAR. Our offering uses new analytical tools. Our suggestion is for readers to view our paper as contribution to set along side earlier work in assessing the dynamic intercourse among the real estate sector, the more general financial sector and the general macro economy.

2. Empirical methods

This paper studies innovation accounting of REITs returns, stock market returns and other macroeconomic variables using the vector autoregression (VAR) model following the lead of Chen et al. (1986). For model reliability we investigate stability of parameters over the sample period. Well-known hypothesis tests for structural change (the Chow test and other traditional tests) exhibit nuisance parameter problems in the case of an unknown break point. The problem with the nuisance parameter arises when the observed data depends on the nuisance parameter only under the null hypothesis but not under the alternative hypothesis. Davies (1987) points out that a structural change test with an unknown break point does not fit into the standard testing framework. Seo (1998) suggests that the conventional LM statistic is not appropriate in the case of an unknown break point because the classical optimality theory does not hold due to the nuisance parameter problem. This paper uses the Sup LM test suggested by Andrews (1993) for a structural

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3 We do not focus on risk premiums explicitly and cite Chen et al. (1986) as supporting a multivariate relationship among macro variables and equity market returns. Our contribution is to isolate the return to REITs from other equity returns and show the relationship between these and macroeconomic variables. For those wanting a more direct link to risk premiums we direct the reader to Ling and Naranjo (1999). Further, our analysis is ex post in the sense that we use historical data to model relationship among variables considered. We do not look at forecasting or ex ante relationships. These, of course, could be explored by focusing study on out-of-sample forecasting performance over a hold-out-sample of observations. We leave this for future work.

4 That is, the conventional likelihood based LM test statistic has a nonstandard distribution in this case.
break test with an unknown break point. The test is general, having asymptotically valid
distributions for a structural break test with an unknown break point. If the existence of a
structural break is identified, the estimation of the break point is pursued using the work of

If a structural break exists over a sample period, empirical estimation using the entire
sample will cease to provide reliable results and hypothesis testing will no longer be valid.
Hendry (1997) and Clements and Hendry (1999) argue that many major failures of eco-
nomic forecasts are due to the structural breaks, which are represented by parameter insta-
bility. In the US several possible points of structural break are notable: the monetary
policy change at the end of 1970s, the federal tax cut in 1981, federal tax reform in

According to the previous research, structural breaks coinciding with policy changes or
economic performance have affected returns on REITs. Ewing and Payne (2005) and Pay-
ne (2003) assume a predetermined structural break in their studies of REITs dynamics.
The break is placed at the beginning of the 1980s, known as the period of the “twin reces-
sions.” Chui et al. (2003) imposes two structural breaks, in 1983 and 1990, based on the
performance of REITs, to examine momentum effects. These studies do not depend on
a formal hypothesis test for the placement of the structural break. An exception in the lit-
erature is the recent paper by Okunev et al. (2000). They study the causal relationship
between real estate and stock markets and apply the structural break test used in Zivot
and Andrews (1992). Their test considers trend/fundamental stationary in unit roots; it
does not consider a test of stability for parameters and possible existence of (multiple)
structural break(s) in the underlying econometric model. They detect a structural break
point at August 1989.

The second contribution of this paper is to apply the Bernanke decomposition on inno-
vations from estimated VARs on sub-periods having no structural breaks. Directed Acyc-
lical Graph (DAG) and the inductive causation algorithms of Pearl (2000) and Spirtes
et al. (2000) are used to better model REITs dynamics over each period. Other studies
investigating REITs do not use these recent DAG innovations. We search for the contem-
poraneous causal structure among innovation series from each estimated VAR and impose
such on subsequent innovation accounting. This allows application of a Bernanke (struc-
tural) decomposition of VAR innovation covariance without using subjective judgment or
the mechanical (and generally unsupported) Cholesky factorization used in earlier gener-
ations of VAR studies.5

2.1. A test of structural break

Curiosity arises concerning whether there might be either a single break or multiple
break points. Possible candidates for breaks are a monetary policy change in the end of
the 1970s (Paul Volker term as FED chair began in October 1979), a tax cut in 1981,
the end of the twin recessions in 1982, the Tax Reform Act of 1986, the stock market
“crash” of 1987, and the savings and loan crisis in the late 1980s and new offerings on

5 There should not be any time pattern of correlation among the innovation series in the multivariate model
(VAR). There will, however, generally be correlations across innovations from different equations of the VAR in
contemporaneous time. Our DAG analysis will model the causal structure behind these cross series innovation
correlations.
REITs starting in 1992. The structural break test is often called a parameter instability test because the test is based on a discontinuity in parameter values. Andrews (1993) suggests using the generalized structural break test with unknown break point to test if an effective break exists in the sample period being considered. The basic time series model is as follows:

$$y_t = x_t \beta_t + x_t d_t \delta + e_t,$$

where $d_t = 1$ if $t > T^*$

$$= 0 \text{ if } t \leq T^*$$

and $T^*$ is a possible break point.

When the time series $y_t$ is explained by $x_t$ in the above equation, the focus is whether the parameter $\beta_t$ is constant or non-constant over time. Based on this idea, the null hypothesis assumes there is no break, $H_0: \delta = 0$. For convenience, a possible break point ($T^*$) is considered as a portion ($\tau$) of total observations ($n$). Hence, the alternative expression of null hypothesis is expressed by:

$$H_{1T}(\tau) : \beta_t = \beta_1(\tau) \text{ for } t = 1, \ldots, n\tau$$

$$= \beta_2(\tau) \text{ for } t = n\tau + 1, \ldots, n.$$  

If the break ($\tau$) is known, the traditional maximum likelihood based tests (Wald, LR, and LM) using a dummy variable, or, alternatively, other stylized parameter instability tests such as CHOW, CUSUM, or CUSUM SQUARED can be used to test significance of the break.

Because $\tau$ appears under the alternative hypothesis only, in the case of an unknown break point, a nuisance parameter problem arises. Following Andrews (1993) a possible break ($\tau$) is assumed to be between 0.15$n$ and 0.85$n$ for the sustainability of the model. Eq. 1 is estimated at every date between observations .15$n$ and .85$n$. After each estimation the Lagrangian Multiplier (LM) statistic is calculated. The maximum LM statistic, over all possible break dates ($\tau$), is the Sup LM statistic for the structural break test.

Because the test statistic has a non-standard distribution, Andrews (1993) examines and reports asymptotic critical values over various numbers of restrictions, up to 20. The calculation of the asymptotic distribution finds the limit process ($= Q_p(\tau)$) in the LM test statistic. For any fixed $\tau$, $Q_p(\tau)$ has a chi-square distribution with $p$ degree(s) of freedom (i.e. the number of parameter restrictions). The approximating distribution of the supremum $Q_p(\tau)$ over $\tau = [\tau_0, 1 - \tau_0]$ is simulated using the Monte-Carlo methods to find the asymptotic distribution. Because this study considers seven endogenous variables including a constant in a VAR, asymptotic distributions for 56 space ($=7 \times 8$) parameter restrictions, i.e. degrees of freedom in the test, are simulated over $\tau = [0.15, 0.85]$.\footnote{See Andrews (1993) for details.}

2.2. Detection of break point including multiple break issue

If Sup LM test results support existence of structural change in a given sample period, a specific break point needs to be found; see Bai (1994, 1997). From Eq. (1), the sum of squared residuals ($S_p(k)$) for all possible breaks are estimated. Then the change point, $T^* = \tau^*n$, is defined as
\[ T^* = \arg \min_{t \leq k \leq (1-r)t_0} S_n(k). \] (3)

Even if a first structural break point is identified and detected, it is still not known whether more than one break exists. When the existence of multiple breaks is suspected, it is necessary to repeat the above procedures—the Sup LM test and detection of break point—over each sub-sample of data.

When structural breaks over the sample period exist, multiple innovation covariance matrices, one for each sub-sample period, can be tested (for equality) following either Box (1949) or Jennrich (1970). Both examine homogeneity of two or more covariance matrices via a chi-square test. In our case (to be described in detail below), the existence of a single structural break, generates two covariance matrices on VAR innovations. If the null hypothesis of homogeneity is rejected, then both covariance matrices found over the two sub-samples can be modeled as different from one another.

2.3. DAG analysis for orthogonality

An issue of orthogonality among the innovations arises in a VAR after a consistent sample period is identified. For accurate and consistent innovation accounting, contemporaneous causal relationships among innovations should be modeled. Early papers using VAR methods (Sims, 1980) applied a “just identified” Cholesky factorization of contemporaneous covariance to find orthogonalized innovations. Bernanke (1986) and Sims (1986) provide “over-identified” restrictions based on the theoretical background information among the variables and thus are able to relax the Cholesky ordering. Swanson and Granger (1997) recommend using Directed Acyclical Graph (DAG) based on observed innovations to provide data-based evidence to supplement the suggestions of Bernanke (1986) and Sims (1986); for further discussions on DAGs and innovation accounting from VARs see Bessler and Akleman (1998) and Hoover (2005). We follow this literature and study the causal patterns from observed innovation covariances with the inductive causation algorithm described below.

A directed graph is a picture summarizing the causal flow among a set of vertices (innovations from our VAR). Arrows are used to represent such flows; the graph \( X \rightarrow Y \) denotes that variable \( X \) causes variable \( Y \). A line between two variables, say \( W \rightarrow X \), indicates that \( W \) and \( X \) are related by information flow but we cannot tell if \( W \) causes \( X \) or vice versa. In this paper we study directed acyclic graphs (DAGs). We do not consider inference on cyclical systems such that information created in one variable (say variable \( W \)) feeds into other variables (\( X \) and \( Y \)), but ultimately returns to its origin (\( W \)); we do not entertain systems such as \( W \rightarrow X \rightarrow Y \rightarrow W \).

The essential notion which allows us to direct causal flow among a set of variables is that of screening-off and its more formal representation in terms of d-separation (Pearl, 2000). For three variables \( E, F \) and \( G \), if variable \( F \) is a common cause of \( E \) and \( G \) so that \( E \leftarrow F \rightarrow G \), then a measure of unconditional association between \( E \) and \( G \) will be non-zero, as both \( E \) and \( G \) have a common cause in \( F \). Pearl refers to such a structure as a “causal fork.” If we measure association (linear association) by correlation, \( E \) and \( G \) will have a

7 One could model feedback in dynamic systems as a DAG by dating variables, so that \( W_t \rightarrow X_t \rightarrow Y_t \rightarrow W_{t+1} \), etc. is a valid DAG representation (see Akleman et al., 1999).
non-zero correlation. If, however, we condition on \( F \), the partial correlation between \( E \) and \( G \) will be zero. Common causes “screen-off” associations between their effects.

An observationally equivalent (to the causal fork) set of “screening off” conditions exist for three variables exhibiting a “causal chain” relationship \( H \rightarrow I \rightarrow J \). The unconditional association (correlation in a linear world) between \( H \) and \( J \) will be non-zero; however, if one conditions on the middle variable \( I \), the conditional association (partial correlation) between \( H \) and \( J \) will be zero. Knowledge of the middle variable in a causal chain will “screen-off” association between the two end variables (the root cause, here variable \( H \), and the sink, here represented as \( J \)).

On the other hand, for the variables \( K, L \) and \( M \) such that \( K \rightarrow L \leftarrow M \), labelled by Pearl as a “causal inverted fork” (Pearl, 2000; page 17), the association conditions differ from those discussed above. Variable \( L \) is a common effect of \( K \) and \( M \). Variables \( K \) and \( M \) will have no unconditional association (zero correlation if we constrain ourselves to linear association); yet, if we condition on \( L \), the association between \( K \) and \( M \) is non-zero (the partial correlation between \( K \) and \( M \), given \( L \) is non-zero). Here knowledge of the common effect \( (L) \) does not “screen-off” associations between its common causes \( (K \) and \( M) \).

Two popular algorithms are considered to search innovations covariances for underlying causal patterns using a directed graph setup. The first candidate is PC algorithm (Spirtes et al., 2000). The algorithm begins with a complete undirected graph with every variable connected to every other variable. It uses tests of independence and conditional independence to remove edges (lines) connecting variables and assigns causal direction based on differences in covariance structures between causal chains and forks on the one hand and causal inverted forks on the other (see Pearl (2000) for discussion of causal forks and inverted forks).

GES (Greedy Equivalent Search) algorithm is a stepwise search over alternative DAG representations using Bayesian scoring function. The algorithm consists of two phases beginning with a representation with no edges (independence among all variables). Edges (connections between variables) are added and/or edge directions (of causal flow) reversed in a structured search across classes of equivalent DAGs if the Bayesian posterior score is improved. The first stage ends when a local maximum of the Bayesian score is found such that no further edge additions or reversal improves the score. From this final first stage DAG, the second stage commences to delete edges and reverse directions, if such actions result in improvement in the Bayesian posterior score. The algorithm terminates if no further deletions or reversals improves the score. Details on the algorithm, justification for selection of the sequencing of edge additions or deletions and mathematics supporting such search are given in Chickering (2002, pp. 520–524). Both PC and GES algorithms are available in the software TETRAD IV (see http://www.phil.cmu.edu/projects/tetrad/).

3. Data

Monthly data from December 1971 through November 2004 are used in our empirical work. Table 1 lists data and sources. The REITs return rate (RT) is calculated by the log

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8 Box and Jenkins (1976) work on univariate time series analysis recognizes these screening-off conditions on a causal chain as part of the “identification” condition of an autoregressive process of order \( p \) in terms of the “tail-off” and cut-off” patterns of the autocorrelation and partial autocorrelation functions.
The difference in the ‘total’ classification REITs index provided by the National Association of Real Estate Trust (NAREIT). The equity return rate (SP) is obtained from the log difference of the S&P 500 index. Inflation (INF) is calculated using the growth rate of the consumer price index. A difference of the logarithm of industrial production index (IP) is used to represent an output growth rate. The term structure (or term spread) of interest rate (TERM) is measured as the difference between the 10 year US Treasury bond rate and the 1 month US Treasury bill rates. The default risk (RISK) is defined as credit spread risk, the difference between Baa and Aaa corporate bond rates. The 1 month rate is also calculated using the 3 month US Treasury bill rate. Because four week US Treasury bill rates are available after the July 2001, the 3 month Treasury bill rate which is annualized is divided by 12 in order to proxy as a monthly rate. The first difference of this 1 month rate is notated by RATE.

The REITs returns, S&P 500 returns, growth rate of industrial production, inflation rate, term spread and default risk are all integrated of order zero (stationary based on non-reported tests of unit roots—the Augmented Dickey Fuller test). Interest rate, however, was found to be non-stationary by our tests and was transformed by first differencing, which did induce a series that was not found to be stationary by our unit root tests.

To explore dynamics of REITs among macroeconomic variables, Payne (2003) uses excess return of REITs which is REITs return rates minus Treasury bill rate following APT. We separate these and include both variables, REITs return and Treasury one month rate, in the VAR system.

We did not pursue questions of cointegration here as all variables except interest rates were found to be stationary. We could have measured variables (REITs returns, equity return, output growth rates and inflation rates) in non-rate form (levels) and may have well found these to be non-stationary and thus potentially the system (in levels) may have been cointegrated. Our strategy may miss possible long run relationships among these series, but should capture the contemporaneous and short run affects (Engle and Granger, 1987). By modeling the data as we did we keep our offering in the same class of models as offered in Payne (2003) and Ewing and Payne (2005).

Table 1
Data definitions and sources

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition (source)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RT</td>
<td>REITs (total) return rates (NAREIT website: <a href="http://www.nareit.com/">http://www.nareit.com/</a> accessed June 2005)</td>
</tr>
<tr>
<td>IP</td>
<td>Industrial production growth rates (DATASTREAM accessed June 2005)</td>
</tr>
<tr>
<td>INF</td>
<td>Inflation rates; the growth rate of US Consumer Price Index (DATASTREAM accessed June 2005)</td>
</tr>
<tr>
<td>TERM</td>
<td>Term structure (Term spread): the difference between the 10 year US Treasury bond rate and the 1 month US Treasury bill rates (DATASTREAM accessed June 2005)</td>
</tr>
<tr>
<td>RISK</td>
<td>Default risk; the difference between Baa and Aaa corporate bond rates (DATASTREAM accessed June 2005)</td>
</tr>
<tr>
<td>RATE</td>
<td>The first difference of one month US Treasury bill rates (DATASTREAM accessed June 2005)</td>
</tr>
</tbody>
</table>

All data are observed monthly over the period December 1971–November 2004. All DATASTREAM data were accessed through Texas A&M library connections.
4. Empirical results

A vector autoregression on our seven variables with two lags (as determined by Schwarz loss, not reported here, but available from the last author) is the focus of our attention with respect to structural breaks.

4.1. Structural break

Using the entire period, January 1972–November 2004, the Sup LM test for structural break with an unknown break point is examined. For the test, 56 restrictions are imposed to consider structural change in all coefficients of the underlying VAR. The results are reported in Table 2. Because the test statistics of Sup LM, 87.66, is greater than 90% of the asymptotic distribution generated, we conclude there is a structural break in the system. Following the Bai (1994, 1997), the break point (T) is found at October 1980 (i.e. new regime starts in November 1980). Possible existence of multiple structural breaks is investigated using application of the structural break test for each sub-sample period, i.e. before and after break periods. By the tests for each sub-sample period, the Sup LM statistic is less than the critical value at 90% of the asymptotic distribution.

A plausible reason for the identified structural break (October 1980) is the monetary policy change induced by the term of P. Volker, as Chairman of the Federal Reserve Bank from August 1979 to August 1987. After Paul Volker was appointed in August 1979, monetary policy was designed to reduce market uncertainty through mitigating high inflation rates. The US economy may well have begun to adapt its behavior to the new monetary policy and the accommodated behavior began to show in our data at November 1980.

As a related aside, we considered an additional structural break test on a reduced VAR, fit with three endogenous variables, rather than the seven variables described above. The result strongly support the existence of structural change between two assets—stock and REITs—returns and interest rates (see model 2 in Table 2).

The tax policy changes—the Tax Cut of 1981 and the Tax Reform Act of 1986—do not account for structural breaks, but monetary policy change (commencement of the Volker years) does. This result suggests no distortion in relationships among risky assets and macroeconomic variables from the tax policy changes or the 1987 stock market crash (or other unknown or unsuspected agents of change).

4.2. Two-period analysis

Hereafter, our entire sample period is divided into two sub-sample groups—pre-break period (January 1972–October 1980) and post-break period (November 1980–November 2004).

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11 The number of restrictions, 56, is based on the number of all coefficients in the VAR—seven endogenous variables and a constant. We have then eight coefficients in seven equations giving us 8 × 7 = 56 zero restrictions.

12 Under a given r = 0.15, the asymptotic distributions of the test are estimated to be 86.42, 90.91, and 98.99 at the 90, 95, and 99% levels, respectively.

13 A sub-sample 1 (before the break, December 1971–October 1980) and a sub sample 2 (after the break, November 1980–November 2004).

14 Other possible structural breaks, the Tax Cut of 1981, the Tax Reform Act of 1986, the stock market meltdown of 1987, the savings and loan crisis in late 1980s, and the 1992 new REITs offerings are considered but not identified using SUP LM.
Estimated variance–covariance matrices (lower triangular elements) on innovations from VARs in pre- and post-break periods are given below as $\Sigma_1$ and $\Sigma_2$ (variable labels are given across the top of each matrix; these labels should be interpreted as correlations arising from innovations in each of the labeled series)

$$\Sigma_1 = \begin{bmatrix}
RT & SP & IP & INF & TERM & RISK & RATE \\
3315.324 & & & & & & \\
1554.521 & 1641.364 & & & & & \\
91.981 & 16.762 & 46.368 & & & & \\
-10.625 & -19.041 & -0.118 & 5.868 & & & \\
5.126 & 0.089 & -0.144 & -0.126 & 0.177 & & \\
0.110 & 0.527 & -0.125 & 0.024 & 0.001 & 0.099 & \\
-7.504 & -1.192 & 0.634 & 0.140 & -0.215 & -0.013 & 0.334 \\
\end{bmatrix}$$

$$\Sigma_2 = \begin{bmatrix}
RT & SP & IP & INF & TERM & RISK & RATE \\
1134.401 & & & & & & \\
703.269 & 1937.285 & & & & & \\
-26.413 & -25.027 & 28.351 & & & & \\
-5.650 & -8.893 & 1.218 & 3.677 & & & \\
-0.762 & -2.555 & 0.155 & 0.028 & 0.112 & & \\
-0.007 & -0.006 & -0.050 & -0.026 & 0.005 & 0.011 & \\
-1.744 & -0.083 & 0.188 & 0.041 & -0.073 & -0.015 & 0.130 \\
\end{bmatrix}$$

Table 2

<table>
<thead>
<tr>
<th>Sample period</th>
<th>Sup LM statistics(^b)</th>
<th>$\tau$(^b)</th>
<th># of restriction(^c)</th>
<th>Critical value(^d)</th>
<th>Break point detection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1(^a)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>December 1971–November 2004</td>
<td>87.66</td>
<td>0.15</td>
<td>56</td>
<td>86.52</td>
<td>90.91</td>
</tr>
<tr>
<td>Sub sample periods</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1) November 1980–November 2004</td>
<td>84.88</td>
<td>0.15</td>
<td>56</td>
<td>86.52</td>
<td>90.91</td>
</tr>
<tr>
<td>(2) December 1971–October 1980</td>
<td>68.65</td>
<td>0.30</td>
<td>56</td>
<td>86.52</td>
<td>90.91</td>
</tr>
<tr>
<td>Model 2(^a)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>December 1971–November 2004</td>
<td>33.39</td>
<td>0.15</td>
<td>12</td>
<td>27.08</td>
<td>29.61</td>
</tr>
</tbody>
</table>

\(^a\) Model 1 is a vector autoregressive using all variables, REITs return rates, stock return rates, industrial production growth rate, inflation rates, term spread, default risk, and interest rate changes. And Model 2 is vector autoregressive using REITs return rates, stock return rates, and interest rate changes, only.

\(^b\) Andrews (1993).

\(^c\) It is a total number of explanatory variables in the VAR.

\(^d\) In model 1, we simulate the critical value using Andrews (1993) for $p = 56$. The critical values of Model 2 having $p = 12$ are replicated from Andrews (1993).

2004). Estimated variance–covariance matrices (lower triangular elements) on innovations\(^{15}\) from VARs in pre- and post-break periods are given below as $\Sigma_1$ and $\Sigma_2$ (variable labels are given across the top of each matrix; these labels should be interpreted as correlations arising from innovations in each of the labeled series).

\(^{15}\) The scales for all elements in each covariance matrices are adjusted by multiplying by $10^6$. 

The homogeneity between both matrices is investigated using the multivariate Box (1949) $M$ statistic, which is a likelihood ratio type test. Under the null hypothesis ($\Sigma_1 = \Sigma_2$), the population covariance matrix $\Sigma$ is $S = n^{-1} \sum_{i=1}^{n} S_i$, and $S_i$ under the alternative, where $S_i$ is the sample covariance matrix, where $i = 1$ for innovations in the pre-break period and 2 for innovations in the post-break period. The test statistic is given here:

$$M = \gamma \sum_{i=1}^{2} (n_i - 1) \log |S_{ui}^{-1} S_u|,$$

where $\gamma = (1 - 2k^2 + 3k - 1)/(6(k + 1)(q - 1)) \left( \sum_{i=1}^{2} \left( 1/(n_i - 1) - 1/(n - q) \right) \right)$ and $S_{ui}$ and $S_u$ are unbiased estimators. $S_{ui} = nS/(n-q)$, and $S_u = nS/(n-q)$. The Box M statistic follows a chi-square distribution having the degree of freedom, $k(k + 1)(q - 1)/2$ (\(=28\)) where $k (=7)$ and $q (=2)$ are the dimension of the covariance matrix and the number of covariance matrices compared, respectively. Values for $n_1$ and $n_2$ are 105 and 289, respectively. That is, the number of observations in each period, where $n = n_1 + n_2$.

Alternatively, Jennrich (1970) provides a homogeneity test of covariances, as well as correlation matrices. The Jennrich test is also a chi-square test with the degree of freedom $k(k - 1)/2$ where $k$ is the number of variables. The test statistic for Jennrich is as follows:

$$J = (1/2) \cdot tr(Z^2),$$

where $Z = c^{1/2}R^{-1}(R_1 - R_2)$, $c = n_1 n_2/(n_1 + n_2)$, $R \equiv (\bar{r}_{ij}) = (n_1 R_1 + n_2 R_2)/(n_1 + n_2)$, and $R^{-1} = (\bar{r}^{-1}_{ij})$. $tr(\cdot)$ and $diag(\cdot)$ are trace and column vector using diagonal elements of the matrix. $R_i$ indicates the sample correlation matrix having sample size $(n_i)$, $i = 1$ (before the break) and $i = 2$ (after the break).

Empirically, the Box $M$ test, shows the value of the test statistic to be 164.42, which is greater than the 99% (one percent significance level) critical value ($\chi^2(k(k + 1)(q - 1)/2) = \chi^2(28) = \text{less than 50}$). The Jennrich test statistic yields a value of 157.22, which is also exceeds the 99% critical value ($\chi^2(k(k - 1)/2) = \chi^2(21) \approx 39$). Hence, both tests for covariance homogeneity show that covariance matrices of innovations between pre- and post-break periods are not homogeneous.

4.3. DAG

In each period, contemporaneous causation is investigated using the GES algorithm applied to innovations on two VARs (one for each sub-period). Resulting graphs are given in Fig. 1. GES algorithm is unambiguous on the ordering of causation offered in panel (A), the pre-break period. We summarize these causal paths using solid directed arrows (\(\rightarrow\)). The three arrows given as dotted lines signify causal flows for which GES is not clear (\(\rightarrow\)). Below we use literature to direct the edges in the manner offered in the Fig. 1. Three common features appear among the edges GES is able to assign (\(\rightarrow\)) between the two periods. First, the algorithm agrees across both periods on the causal flow from TERM to

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16 The Box $M$ statistic used here is adjusted using $S_u$ and $S_{ui}$. From the likelihood ratio, $-2 \ln \lambda = n \ln |S| - 2n_i \ln |S_i| = \Sigma n_i \ln |S^{-1}_i|$, if $n_i$ is small, this ratio gives too much weight to the contribution of $S$ (see Mardia et al., 1979, pp. 140).

17 To compare correlation matrices through the Jennrich test, the distribution of test statistics changes to $J = (1/2)tr(Z^2) - diag(Z)/S^{-1} diag(Z)$ but is still an asymptotic chi-square distribution with df = $k(k - 1)/2$ where, $S = (\delta_{ij} + \bar{r}_{ij})$ and $\delta_{ij}$ is Kronecker delta (i.e. identity matrix)—see Jennrich (1970). For recent applications of Jennrich test, refer to Bha (2001) and Carrieri et al. (2003).
RATE and from RISK to RATE. These two arrows appear reasonable as short-term interest rates can be explained as an adjustment process based on term structure and default risk spread information. Second, the shock in inflation is instantaneously independent of other variables in both periods. And finally, new information arising from (shocks in) the term spread and default risk can be considered contemporaneous root causes and RATE a contemporaneous “sink” in both periods.

GES finds differences in graphical structures of pre- and post-break periods. Real estate shows itself as a stronger casual agent in the post-break period compared to that in the pre-break period, as GES algorithm finds a directed edge running from RT to RATE in period two. Also, in the second period, three undirected edges (RT-IP, SP-RT, and TERM-SP) are found that were not present in period 1. We draw these as dotted lines in panel B, with the direction of causal flow based on the analysis given below.

On period 2 innovations, GES algorithm finds a relationship exists but cannot assign causal direction on the three sets: RT-IP, SP-RT, and TERM-SP. These undirected edges are consistent with eight possible directed causal relationships. These possible cases can be segregated into equivalent classes. Equivalence is conceptually defined in two ways: distributionally equivalent and independence equivalent. When two DAGs exist, both are

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Fig. 1. Contemporaneous causal diagrams. Note. The abbreviations indicates RT (REITs returns rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).
distributionally equivalent if they have the same probability distribution (if the joint distribution on the set of variables studied is the same on two alternative DAGs those DAGs are distributionally equivalent). In contrast, both models are independence equivalent if they have same independence conditions. Generally, distributional equivalence and independence equivalence are not necessarily the same, but independence equivalence accompanies distributional equivalence in the case of a multivariate Gaussian model which this paper applies (Chickering and Meek, 2002; Chickering, 2002; and Spirtes, 2005).

Among the three equivalent classes in Fig. 2, the first panel—having four equivalent DAGs—is optimal with respect to chi-square test statistics and Schwarz Information

\[ \chi^2_{df=15} = 27.4571, \text{ SIC} = -86.9465 \]

\[ \chi^2_{df=15} = 28.6904, \text{ SIC} = -86.9414 \]

\[ \chi^2_{df=15} = 30.2421, \text{ SIC} = -86.9360 \]

Fig. 2. Equivalent classes in the post-break period. Note. The abbreviations indicates RT (REITs returns rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).
Criterion. Each DAG in the first equivalent class scores the same on both the chi-squared test and Schwarz loss, but there is no agreement about contemporaneous causal relationships among RT, SP, IP and TERM. To select one out of the four equivalent DAGs, we rely on previous literature.

A number of studies explain stock market movements in terms of predictive ability. While predictive doesn’t necessarily inform us with respect to contemporaneous information flow, we rely on it to sort among the four graphs of Fig. 2, panel A. Keim and Stambaugh (1986) and Fama and French (1989) suggest term spread to predict movement in the stock market. Campbell (1987) shows that term spread of interest rates predicts excess stock returns and excess returns on t-bills and bonds. Also, Avramov (2002) and Avramov and Chordia (2006) provide that a term spread is useful to forecast a stock return.

There is also a literature noting the significant linkage between real estate and real output. Goodhart and Hofmann (2000, 2002) and McDonald (1996) argue that real estate can be considered an input into the commercial and industrial production processes. The only model in equivalent class 1 of Fig. 2, which is consistent with both literatures (spread predicts stock returns and real estate returns predicts production processes), is model (4). This is thus our DAG on innovations for the post-break period. It means that REITs is an information source for RATE and IP after the break; while before the break REITs received information from IP and TERM (the TERM edge does not appear after the break).

4.4. Impulse response functions

The dynamic differences of characteristics between returns on REITs and stocks are identified using the impulse response function analysis (see Fig. 3). Response functions give information on the direction and significance of dynamic responses for a 9 month horizon following an initial shock of each variable.

A shock to the stock return rate positively affects the return rate for REITs, contemporaneously and dynamically in both the pre- and post-break periods. However, the inverse influences are statistically insignificant for both periods.

Returns on REITs and stocks show insignificantly negative responses to a shock in inflation in both periods. Fama and Schwert (1977) investigate an inflation effect on asset returns for a number of assets. They conclude that common stocks seem to perform poorly as a hedge against both expected and unexpected inflation. Adrangi et al. (2004) show negative correlation between a real return of REITs and unexpected inflation. One of the well-known relationships regarding REITs and inflation is that both are negatively dynamically correlated (Lu and So, 2001). Even though the negative response of REITs returns to inflation shock is barely insignificant, this dynamic has important implications for market expectations. Once unexpected inflation is realized, market participants would expect the Federal Reserve Bank to increase interest rates; this has reduced incentive to change portfolios to real estate and stocks. However, this inflation factor also seems not to be useful for discriminating dynamics of returns on both assets.

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18 Because GES algorithm has attained the optimal BIC, any other improvement in the first equivalent class is not available from the second step of GES algorithm.

19 A contemporaneous causal relationship among innovations is applied to obtain orthogonal innovations.
The dynamic responses in returns on REITs and stocks from a term spread shock are consistent in each period. However, there are considerable differences in the dynamics between both sub-samples (before and after the break). Before the break, both responses show significantly positive responses to a term spread shock. In contrast, they show com-

Fig. 3. Impulse responses to one S.D. innovation. Note. The forecast horizon is measured in month and is given on the horizon. The vertical line shows magnitude of response. The dotted line indicates confidence band, \( \pm 2 \cdot S.E \). The abbreviations indicates RT (REITs returns rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).

The dynamic responses in returns on REITs and stocks from a term spread shock are consistent in each period. However, there are considerable differences in the dynamics between both sub-samples (before and after the break). Before the break, both responses show significantly positive responses to a term spread shock. In contrast, they show com-
commonly negative instantaneous responses and recovery dynamics after the break. Generally, a positive change of term spread is known as a signal for future inflation or future economic expansion. Contrary to the effect of the former signal, the latter signal perhaps implies increases in demand for assets.

A proxy hypothesis of Fama (1981) says there is a negative relationship between expected inflation and real activity and a positive relationship between expected inflation and real stock. However those relationships are not clear because unexpected inflation shock is considered as well as nominal stock return.
Table 3
Forecast error variance decompositions

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(continued on next page)
The responses of real estate return and stock return to shock in the short run interest rate change (RATE) show an interesting difference. A shock to interest rate change significantly affects only stock return before the break and only real estate return after the break. In other words, the negative response of real estate return to interest rate shock becomes significant, but the relationship of stock return to interest rate shock is not significant from zero after the break. Tufte and Wohar (1999) show a positive relationship between stock returns and interest rates in the financial industry. A negative response in real estate return to an interest rate shock becomes significant after the break.

### 4.5. Forecast error variance decompositions

Forecast error variance decompositions over a twelve month horizon are shown in Table 3. Here we partition the forecast uncertainty in each variable to information arising in each of the seven series. Any particular panel shows the uncertainty (standard error of the forecast error) associated with each forecast horizon studied (0, 1, 2 and 12 month horizons) and how it is partitioned (decomposed) into earlier information shocks arising

<table>
<thead>
<tr>
<th>Horizon</th>
<th>SE</th>
<th>RT</th>
<th>SP</th>
<th>IP</th>
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<th>RISK</th>
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</table>

*Note. The abbreviations indicates RT (REITs returns rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).*
in each of the seven series. So for example the first panel of Table 3 gives the decomposition on REITs returns (Variance Decomposition of RT). At the 12 month horizon the standard error (square root of the forecast error variance) is 0.04. Earlier information shocks from (innovations in) the REITs returns account for 71.44% of the uncertainty in REITs, 22.57% of standard error of the forecast in REITs at the twelve month horizon is due to information arising in SP500 returns, 0.72% is due to information arising from Industrial Production, 1.13% die to Inflation, 2.04% to Term spread, 0.89% to new information arising from default RISK and 1.21% is due to variation in the short term interest RATE.

One of the most apparent features in Table 3 is that stock and real estate returns are more exogenous in the post-break period relative to in the pre-break period. That is, the share of variation explained by their own innovations increases in the post-break period. For example, the shares of real estate return variation explained by its own innovations are less than 50% at all listed horizons before the break and over 70% after the break. This finding—a small portion of other variables in accounting for uncertainty in REITs returns and stock returns—could be explained by the change in structure in the macroeconomy following the Volker appointment. The new policy may well have made the macroeconomy less a source of information—new information. Thus REITs returns are not responding to volatilities originating in the macroeconomy as they once did. Further, the evidence from our GES search shows that REITs may have a stronger affect on the US economy over the post break period than hitherto.21

Other interesting changes in forecast error variances related to real estate between the two periods are the less importance of real estate returns in explaining variation in interest rates in the post break period (note the last panel in both sections A and B of Table 3). Here we see that over the 1972–1980 period REITs explain about 6–7% of the uncertainty in short-term interest rates; while for the 1980–2004 period this percentage drops to less than 3% at all horizons. Related to the issue listed about, in the pre-break period returns on SP 500 explain a considerably larger proportion of the forecast error variance of REITs returns (≈38 to 48%) than do SP 500 returns on post break data (≈22%).

21 As all models in equivalence class 1 of Fig. 2 are observationally equivalent one might very well argue that there is sufficient evidence to explore the influence of the REITs on equity returns under the flow of contemporaneous information from REITs innovations to innovations in the S&P500 (allowing REITs to actually move information in the more general equity market in contemporaneous time). Using model (1) of Fig. 1 we observe the following partition of forecast error variance in the REITs and S&P500 at the 12 month horizon:

<table>
<thead>
<tr>
<th>Variance decomposition of REITs</th>
<th>Horizon</th>
<th>SE</th>
<th>RT</th>
<th>SP</th>
<th>IP</th>
<th>INF</th>
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<th>RISK</th>
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<table>
<thead>
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<th>Horizon</th>
<th>SE</th>
<th>RT</th>
<th>SP</th>
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<td>22.79</td>
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<td>0.07</td>
<td>0.05</td>
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</tbody>
</table>

This last result shows that over the post 1980 break period returns on REITs may have had a non-trivial affect on overall equity market performance (22.79 percent of the uncertainty in SP500 returns at a twelve month horizon can be explained by information arising in REITs returns in the post break period). Similar partitions are found using model (2) for Fig. 2. Details are available from the third author.
5. Conclusions

This study describes an econometric model, fit over 1971–2004 monthly data, on movements of returns on REITs, returns on equities, and several related macroeconomic variables (inflation rate, growth rate of industrial production, default risk, and term spread).

A single structural break is detected at October 1980. This change is possibly due to the monetary policy changes following the 1979 appointment of Paul Volker as Chair of the Federal Reserve Bank. The structural break point found here is different from previous studies; Chui et al. (2003), Ewing and Payne (2005), and Payne (2003) assumed break points at December 1989, December 1979, and September 1982, respectively, without a test. Okunev et al. (2000) found a break at July 1989, but they did not consider a comprehensive test of stability for parameters. We are aware of no study that tests for the existence of multiple structural breaks. We find only one such break, October 1980.

Our results point to REITs having a stronger influence on the US economy over the post-October 1980 period, relative to the pre-October 1980 period. In our study of contemporaneous causality on “new information” arising in each series under study (innovations in REITs, SP500, Inflation, Term Spread, Default Risk, Short Term Interest Rates and Industrial Production), we found REITs to be an information “sink” before the 1980 break date, receiving new information from the SP500, Industrial Production and Term Spread, but sending out no information to other variables studied. After the break date we find clear evidence that new information associated with returns on REITs leads Short Term Interest Rates. Further, there is also evidence (which we cannot reject, see footnote 21) indicating that over the post-break period new information arising from returns on REITs may actually lead the SP500.22 These results suggest that real estate investment has played a more exogenous role in the US economy after the 1980 break date.

References


22 While our results clearly indicate the macroeconomy appears to be looking at information emanating in REITs markets in the second (post-break) period, we should caution that REITs returns may be proxying for more fundamental variables that we have not included in the analysis.


Davies, R.B., 1987. Hypothesis testing when a nuisance parameter is present only under the alternative. Biometrika 74, 33–43.


