Commoll Features in U.K. Commercial Property Returns

by

Bryan D. MacGregor

Centre for Property Research

Department of Land Economy

University of Aberdeen

and

Gregory M. Schwann7

Real Estate Research Unit

Department of Property

University of Auckland

December, 1998

7 We invite comrnelts on tbis workillg paper.

7 Please send all correspondence regarding this paper to Greg Schwann, Private Bag 92019, Auckland, New Zealand, Tel: +64-9-373-7599 Ext. 4819, Fax: +64-9-308-2314, g.schwann@auckland.ac.nz.

Abstract

Ve examine in this paper the degree of short run co-movement in U.K. commercial roperty returns by estimating regional common cycles. Thirty-nine rate of return eries are used. These series span the economic planning regions of the U.K., and over the retail, office and industrial sectors. The empirical modelling follows the vork by Tiao and Tsay (1985), Engle and Kozicki (1993), Vahid and Engle (1993, 994) and Engle and Issler (1995). Bivariate and multivariate common eature/common cycle tests are performed and the reduced dimensional VAR model is stimated by FIML.
'he existence of common features is important in the study of commercial returns for wo reasons. First, when common features exist, uncovering these common features bnhances our understanding of the returns generating process. Moreover, the .dividual returns series may be **modelled** by a reduced dimensional system of rommon cycles. Pragmatically, it means models that are more parsimonious can be ssed, which is a virtue when time series are short. Second, the common features ,enerate a set of portfolios, which have no systematic risk and satisfy the martingale
roperty.

1.0 Introduction

2.0

In this paper, we examine the degree of co-movement in U.K. commercial property realrns by estimating regional common cycles for the U.K. retail, office and industrial sectors. Our working hypothesis is that a large *action of the fluctuations in commercial property reaurns may result from a small number of core disturbances. These disturbances are transmitted from one region to another and from one sector to another. This paper applies the concepts and methodology developed in the large literature on real business cycles to the pricing of regional property assets. The empirical model follows the work by Tiao and Tsay (1985), Engle and Kozicki (1993), Vahid and Engle (1993, 1994) and Engle and Issler (1995).

Our primary objective is to test our working hypothesis by determining if one or more common cycles exist. This is huportant since isolating common cycles is equivalent to isolating the fundamental flucauations in the property sector from the myriad of national and regional factors potentially affecting property returns. Once isolated, future research can focus on the causes of these key factors. In this respect, this research is analogous to understanding the number of risk factors underlying asset returns. Common cycles are also important to portfolio management. By definition, they are systematic risk factors that can not be diversified away in inter-regional property portfolios. Hence, one needs to understand common cycles to properly assess the diversification possibilities in the property asset class (Harbert 1998).

There are two reasons for believing that common features/cycles exist in the U.K. realrns to property. First, the rates of reaum may move together because they reflect a common national real business cycle. Since the demand for property is a derived demand, fluchuations in the real value of sectoral output will have a direct impact on property rental rates and on the measured rates of realm. Consequently, if the national business cycle dnves regional flucauations in output, there will be a high degree of co-movement in the regional rates of return. Second, equilibrium in the national capital market will tend to force the regional rates return to a cornmon risk adjusted rate of return. Market-wide shifts in asset returns or nsk will be milTored in all markets, including regional and sectoral markets for property.

addition to these two reasons for believing in co-movement, the basic empirical evidence ^.-o suggests there is co-movement in the regional rates of retmn for each property type and co-movenlent in the sectoral rates of return across regions. Figures 1, 2 and 3, which depict real regional rates of retun] to retail, of fice and industrial properties, do show co...ovement. Most of the rates of retum have peaks in the late 1970s,1ate 1980s and mid 1990s, and they have troughs in the early 1970s, 1980s and 1990s. These features conTespond tith the U.K. business cycle. The principle difference among the series is in the amplitude of the fluctuahons. In general, the oMce sector has the widest fluctuations, followed by the tail and industrial sectors. There does not appear to be a consistent pattern of leading or lagging sectors. rO this point, we have stressed theoretical and empirical reasons for the existence of common rends or cycles in the time senes of regional property retunns. There is also au econometric eason for testing for common trends or cycles. Since co-movement among time senes ,.ldicates the existence of common components, adding this infonmation to the model makes possible to construct a more parsimonious and efficient time series model. This is a virtue ,vhen time series are short, as is the case in many property studies.

Po illustrate this idea, consider two property time series, y,, and y2,, which are dependent on he outcomes of single variable x, via the data generating process

$$\begin{bmatrix} Y_{1t} \\ Y_{2t} \end{bmatrix} = \begin{bmatrix} \alpha \\ 1 \end{bmatrix} + \begin{bmatrix} \xi_{1t} \\ \xi_{1t} \end{bmatrix}$$

The time series x, may be serially conTelated, but the disturbances (41l, 42,) afe stnctly ontemporaneous. It is cleat from the data generating process that tbe dependent series, (yt,, 2t), will inherit the time series properties of the independent series, x,. Hence, one can obtain a complete descnption of the joint process by modelling one of the time senes and estimating the transfer parameter a. This insight is the basis of the reduced rank regression models developed by Anderson (1951), Velu *et al* (1986), Ahn and Reinsel (1987, 1988), Pefia and Box (1987) and Ahn(1997).

A point worth noting is that, while the dependent series in (I) may be serially correlated, the variable y,t-ay2, will be serially unconrelated; more specifically, it is uncorrelated with the information available to time t- I . This property is the basis of the tests for common features developed by Vahid and Engle (1993), based on the earlier work by Tiao and Tsay (1985, 1989).

The rest of this paper is organised into eight sections. In the next section, section 2, we review the literature related to our reasons for believing in common cycles. In section 3, we describe the econometric methodology for testing for common features in stationary time series. These tests are the core of the paper. Because this methodology is not well known, we describe it at length. In section 4, we develop simple inter-regional asset pricing model. We develop the model to show that our region-on-region analysis is a valid asset pricing framework. The model also aids our interpretation of the results. We describe our data set in section 5. We begin the presentation of our results in section 6 with the presentation of the descriptive statistics for the rates of retunn we are analysing. This section also contains the Phillips-Perron unit root tests we use to establish the stationarity of our time series. Further, we present our findings concernmg the univariate time series properties of the time senes. In section 7, we give the results from our common feature tests. These tests suggest that there is at least one common cycle underlying each of the property sectors. The results in section 6 enable us to specific a common features model for each property section. In section 8, we give the estimation results for these models. We conclude in section 9.

2. **Related Literature**

Vhile Figure I - 3 above illustrate co-movement, this does not imply, in itself, that the coDvement results from the transmission of a natlonal business cycle from region to region. .ong and Plosser (1983) demonstrate that measured co-movements in sectoral outputs can be nP result of serially uncorrelated and cross-sectionally independent productivity shocks. In ir model, a 'national business cycle' results from the sum of the independent sectoral Froductivity shocks. That is, there is a problem of causation, which must be sorted-out statistically ver the past fifteen years, a number of studies have examined the causation of sectoral and egional business cycles. These studies are part of the economic literature on real business ~cles. Long and Plosser (1987) show that the output innovations for sectors of the U.S. conomy can be explained by a common set of aggregate disturbances. Durlauf (1989) .ows that the sectoral outputs in the United States are cointegrated; that is, they share a ommon set of stochastic trends. Pesaran *et al.* (1993) examine the relative persistence of lational macroeconomic shocks and sectoral shocks on national output. Their empirical esults show that sectoral shocks have more persistent affects on national output. Engle and ssler (1995) also report that sectoral outputs are cointegrated. In addition, they demonstrate Lat the sectors of the U.S. economy share a small number of common cycles, as well as laring common trends. Consequently, the sectors of the U.S. economy have very similar ryclical behaviours.

^' e commonality of European sectoral disturbances have also been investigated. Stockman 1988) examines the annual growth rates of industnal production in two-digit manufactunng ndustries in seven European countnes, including the U.K. He decomposes the growth rates -to nation-specific disturbances and sector-specific disturbances. His results show that there Lre significant national (regional) effects common to the industnes in a nation and significant rommon industry effects across the European nations studied. Caporale (1997) examines the

relative importance of aggregate and sectoral output shocks in the U.K. His analysis is similar in spirit to Long and Plosser (1987). Caporale finds that a significant percentage of the fluctuation in U.K. output is due to a single unobserved component.

These U.S. and U.K. studies point to significant commonality in regional or sectoral output fluctuations. This commonality may be in either the trend or cycle components of the series. Thus, we expect the measured co-movement in the sectoral retums to property to be generated, at least in part, by a common set of output factors.

We turn now to the capital market reason for believing in the commonality regional returns A central tenant in modern finance is the trade-off between risk and retum. This principle is independent from location and, therefore, applies equally to properties located in London or Scotland. An implication of this principle is that the appropriately nsk-adjusted regional property returns will have a common equilibrium value.

Unfortunately, there is little evidence on regional asset pncing in the finance literature. Most financial instruments are national and aspatial. However, the integration of world capital markets has spawned a substantial literature on stock market integration from which we may take some evidence on spatial arbitrage.

Taylor and Tonks (1989) examine the integration of U.K. and overseas stock markets following the 1979 removal of U.K. exchange controls. They find that the abolition of the controls increased the long run integration of the U.K. market with other markets. No short run increase in integration was evident. Lai *et al. (* 1993) use a VECM to study the integration of the New York and Tokyo stock markets. They find evidence of both short run and long run co-movement between the two markets. They also find that the degree of integration has increased over time, particularly after the 1987 crash. Chou *et al.* (1994) obtain results similar to Lau *et al.,* but for an expanded set of stock markets. This study finds that the stock price indexes for the U.S., Canada, the U.K., France, Germany and Japan are all cointegrated and that the cointegration relationships are getting stronger with time.

tichards (1995) argues that the previous studies are statistically tlawed because they use ymptotic critical values when testing for cointegratiml. He advocates the use of small iample cntical values. Nevertheless, when he examines the co-movements of the stock narket indexes for 16 national equity markets, he finds that they contain a common world romponent, a common permanent country specific component and a country specific .ommon cycle. Conflicthig results emerge frmn Gallagher's (1995) study of the roh1tegration of the Irish, U.K. and German stock markets. He finds no long or short run elationship between the Irish market and the other two markets. He suggests that this is due n the inefficiency of the Irish market.

These studies indicate that: the international stock markets are integrated, that the degree of :egration is increasing over time with the globalisation of financial markets, and that the 'egree of integration depends on market liquidity and market efficiency. It is not clear vhether these results carry over to property markets. The price discovery literature suggests hat they may (See Chau *et al.* for a review of this literature.). This literature supports the iew that the stock and property markets are substantially integrated. One can argue, ~ erefore, that the spatial integration exhibited by equity markets may be transferred to)roperty markets. However, the price discovery literature also indicates that, as is the case vith equity markets, the degree of integration depends on market liquidity and market bfficiency. The inherent illiquidity of property markets may prevent their spatial integration.

3.0 **Common Features in Stationary Time Series**

Uthough the idea of determining common components in multivariate time series is not a ~ew one, the econometric techniques needed to determine these components have been ' xveloped largely over the past decade. The largest advances have been in cointegration nethods (Engle and Granger 1987; Stock and Watson 1988, Johansen 1988,1991). These methods focus on the determination of the common trends in a nonstationary multivariate time series and are relatively well known. Parallel, but less well known advances have occurred in the determination of the cofeatures and common cycles in stationary multivariate time series (Engle and Kozicki 1993, Vahid and Engle 1993). We focus on the latter for the simple reason that the real returns to property in the U.K. are stationary.

Since the terminology in the common cycle studies is not well known, some definitions are in order. Our discussion follows Vahid and Engle (1993). We assume that the property returns

r,=(rl,, ..., rN,) have the finite VAR(p) representation:'

A(L)rt =F+Et A(L)=I-AiL-A2L2-...-ApLP

(2)

where the Aj's are NxN matrices, p is an Nxl vector of constants and e, is a Nxl vector of white noise disturbances. The property returns are said to have a cycle

if they display persistence; that is, if the time series of returns is forecastable based on the past regional returns. According to this definition, both random walks and non-forecastable series do not
cycle.

The definition of a cycle is problematic when studying financial time series. It requires forecastability of the series, which violates the weak form efficiency criteria. We offer two justifications for considering cyclic financial time series: one empirical and one theoretical. First, we are dealing with property return cycles, which are intrinsically long run cycles. Over a comparable period of two to five years, even equity retums are forecastable (Campbell and Shiller 1988, Fama and French 1988, Shiller 1984). Indeed, this is the starting point for a large literature in finance examining time vanations expected asset retums. Campbell *et al.* (1997, chapter 7) give an excellent review of this literature. Theoretically, weak form efficiency is neither a necessary nor a sufficient condition for rationally determined asset prices (Lucas 1978). Asset retums must be suitably risk adjusted for the martingale property to hold. The presence or absence of persistence in measured returns does not imply anythhig about market efficiency.

Cycles are a product of what Engle and Kozicki (1993) refer to as the features of the senes. rhe elements of r, have a serial correlation common feature if a linear combination of the ments, atr,, exists that is an innovation with respect to the information set at time t (i.e., all observed prior information). The linear combination is termed a cofeature combination and :he vector a is termed a cofeature vector. There can exist s<N linearly independent cofeature ~^ectors. The collection of cofeature vectors folms an Nxs matrix, which we also denote by x. The range space of the matrix a is called the cofeature space. Common cycles are in the ompliment of the cofeature space and hence there are N-s common cycles.

then the data generating process has the VAR representation (2), a serial correlation .ommon feature exist when:

$a'A_j = 0$ Vi (3)

Phese restnctions require all the A matrices to be less than full rank and to have overlapping eft null spaces. These properties mem that the linear combinations of the retums a'r, are <~correlated with any linear combination of the past information Z't_l E (rt'_l . . ., rt'_p).

vsay (1993) and Vahid and Engle (1993) advocate a test of these orthogonality conditions sed on the canonical correlations between r, and t.l. Recall that a canonical correlation is 1 correlation between two cmonical variables formed as linear combinations of r, and Z,.~, espectively. By definition, when the orthogonality conditions (3) hold, the cmonical .orrelation between the two variables should be statistically close to zero. Further, the rights in the linear combination with rt are a cofeature vector. Now, recall that the ordered anonical correlations (smallest to largest) represent the correlations between a collection of nutually uncorrelated canonical variates. Thus, when s is the rank of the cofeature space, the irst s canonical correlations will be statistically insignificant.

The idea of a serial correlation common feature, which we have just described, is a special case of the scalar component model (SCM) developed by Tiao and Tsay (1989). The VAR model (2) with the restrictions (3) is a scalar component model of order (O, O). The notation (O, O) denotes the autoregressive order and moving average order, respectively, of the linear combination atr,. The canonical correlation test we described is a test an SCM(O, O).

Before presenting the details of this test, we need to examine the issue of synchronicity. The common features we have described entail synchronous co-dependence between the time series.2 Specifically, the impulse responses of the time series are collinear. Since there is ample evidence of leads and lags in economic adjustments, particularly in regional adjustments, the idea of common features appears to have limited utility. Fortunately, one can extend the concept of common features to encompass non-synchronous co-dependence. Vahid md Engle (1993b) add non-synchronous co-dependence to the model we have descnbed above by allowing the impulse responses to have memory. They accomplish this by considering scalar component models of order (O, q), where q is non-negative and (hopefully) small.

Assuming that the data generating process for the regional returns is a SCM(O, q), the Tiao and Tsay test statistic for the null hypothesis that the rank of the cofeature space is at least s is

C(m, q, s) = -(T - m) E In (I - i)

j=l dj(m,q) (4)

Under the null hypothesis, C(m,q,s) has a x2 distribution with s2+snm-sn degrees of freedom.

The vj(m, q) in (4) are the ordered squared canonical correlations between r, and

Zm t_q 1 2 (rtt-q-l . . ., rtt-q-p). 3 The number m equals the number of lags needed to form

Zm,q-l Here, m = p+q. The values di(m, q) are defined as

di(m,q)=1+2Epk(v(r)(i))pk(v(Z)(i)) (S) k=l

where pk(-) is the lag-k autocorrelation for the vanables v(r)(i) and v(Z)(i). The variable v(r)(i)

= ej'rt with ei being the eigenvector correspondblg to the ith squared canonical correlation

vi(m, q). The variable v(Z)(i) is defined similarly.4

4.0 **A Simple Financial Model**

The preceding section is purely econometric. It defines cofeatures and common cycles, but does not provide any intuition into what these mean for the U.K. regional property returns. In this section, we fill this gap by developing a simple inter-regional asset pricing model to aid the interpretation of our results.

An inter-regional asset pricing model may be derived from a variety of capital asset pricing models: CAPM, APT, ICAPM or by using an intertemporal equilibrium model. We begin with APT because a core idea in APT, that asset returns depend on a set of (potentially latent) pricing factors, corresponds directly with the idea that asset returns contain a set of latent common features. Hence, a test for a serial correlation common feature is a test for a specific type of pricing factor. Under APT, with exact factor pricing, the retunl generating process for the regimoal property returns is

K

ria = Ao~+ ~,pki(fkt+~kt_11k)+_it i=l,...,N k=l

(6)

where rit is the return on the property in region I for time t, A0, is the model zero-beta return for time t, ~ki is the factor sensitivity for properties in region i to the systematic risk factor fkt,

Xk, is the nsk premium for the kth risk factor, F is the unconditional mean for the kth risk factor, and Ejt is the unsystematic risk specific to a property in region i at time t. In this form of the APT return equation, the systematic risk factors do not need to be traded portfolios of properties and may include macroeconomic or business cycle factors.

With loss of generality, we assume that pljwO, and use this equation to solve for the first risk

factor. Substituting this value for f,t into (6) gives

K

rit =(t _ij)~Ot +_ijrjt + 2 (~iki 9ij~b)(fkt

+~kt_Rk)+(Eit_oijEjt) (7)

where Oq = DI J: ,j is the sensitivity of properties in region i to risk factor one, relative to properties in region j. Equation (7) relates the return from properties in region i to those in region j, plus a residual set of risk factors. When there is only one risk factor, as in CAPM, the third term in (7) vanishes and we have the pairwise inter-regional asset pricing equation

rjt = (I_njj)kOt + _urit + (Eit OijEjt)

It is easy to see from this equation that when the retums series Ij and rj are persistent, the vector (1, -Ojj) is a cofeature vector.

(8)

The third term will vanish also when factor sensitivities for regiol i are proportional to those in region j; that is, when, ph/tpkj = O for all k=l ,. . .,K. This should not be surprising, as these are the Hicks' aggregation conditions. They permit one to aggregate the K risk factors into a single composite nsk factor. This creates a potential difficulty in any empirical work relatulg the regional returns. If the factor sensitivities are *approximately* proportional,5 a test of the number of systematic risk factors will not tend to reject the null hypothesis, K=l.

In the general case, when K>l and the risk sensitivities are not proportional, one may continue to solve for the risk factors in terms of the regional returns. All of the systematic

risk factors are determined by K linearly independent returns. This establishes that a general inter-regional asset pricing equation has the form

K

rit = rO + EI7ijrjt + nit

jXi

(9)

1 nus, in a K factor model, one can price the returns to one region in terms of the returns to K other regions. Requiring that the other regions have linearly independent returns implies that the regional returns span the risk factors. Thus, if a systematic risk factor exists that is specific to one region only, the return to the region with this risk factor must appear in the pricing equation. Again, the vector (1, -Yil,- _, -YjK) is a cofeature vector when the returns are -ersistent. It also shows that a K factor model implies a K dimensional cofeature space.

Of course, equation (9) is a very poor estimator of the systematic risk factors. It is not a minimum vanance estimator and depends on which K regional returns are used to form the actors.7 From an econometric viewpoint, it is better to use the cross-sectional information 1 all the retlrns to estimate the factors. The two statistical methods most ohen used to estimate the factors are factor analysis and principal component analysis. Both methods use all the return information to yield a linear estimator for the systematic risk factors. Substituting these estimates of the risk factors into equation (6) gives a linear pricing equation identical to equation (9), except that the retums in regiln i are priced in telms of the returns to *all* other regions.

None of the results presented above are particularly novel. We present them in order to illustrate four points. (I) It is legitimate to price the retums in one region as a function of the returns in a set of other regions. (2) If the number of systematic risk factors affecting egional property retums is small, a correspondingly small number of independent other -egions is needed to generate the retums in any one region. (3) In a regional context, the esting for the number of systematic risk factors may be done by testing for the number of independent regions needed to price a system of regional returns. (4) When a subset of regional returns is persistent, the estimated cofeature vectors for the system are estimates of the factor weights in a regional APT model and the rank of the cofeature space equals thc number of underlying risk factors.

5.0 Data

This saldy is based on the annual property returns for the period 1973 to 1997 contained in the Hillier Parker data set.8 The data set contains rates of return for retail, of fice and industrial properties for the ten economic planning regions of the United Kingdom, plus London. Because the geographic subdivision of London differs by property type, there are 13, 15 and 11 areas for the three property types, respectively. These data are available as semi-annual or annual observations. We have opted for the annual data for two reasons. First, the real business cycle literature (reviewed above) and the regional economics literature show that regional equilibration is a slow process. Therefore, it is desirable to examine the process over as long a period as possible. The annual series is the longer of the two series. It starts in 1973 while the semi-annual senes starts in 1977. Second, we are primarily interested in the behaviour of returns over the business cycle. Using higher frequency, semi-annual data does not add to our understanding over this time frame and may add confounding high frequency noise. While the annual data better matches our objective, it does confine us to 25 observations and limits the statistical power of our tests.

The regions in the data set are pre-defined. The regions are unequal in size and in the number of properties covered. This means the return series embody varying levels of contemporaneous aggregation. Since contemporaneous aggregation tends to increase the order of the autoregression (Lutkepohl 1984), the larger areas should have longer autoregressive processes. While varying leveis of aggregation may affect our results, we caumot correct for it.

We deflate each of the retum series by the national rate of inflation to create a real returns series. The inflation series are from the IMF country data set for the United Kingdom. We are working with real returns in order to focus on the regional fundamentals affecting regional returns (e.g., demand, construction, and productivity), rather than Fisher effects and the regional transmission of inflation.

6.0 **Descriptive Statistics**

Table I contains the summary statistics for our real rate of retum series by property type. The statistics are calculated for all the regions and over the 25 years of returns in our data set. From the meaul returns, we see that retail properties performed the worst (7.6%), followed by of fice properties (8.4%). lndustrial properties performed the best (10.3%). The three property types are also quite different in terms of their underlying risks. Of fice properties are the riskiest, with a standard deviation of 21.4% and a support of -51.7% to 119.8%. Retail properties and industrial properties are less risky, with standard deviations of 18.2% and 17.1%, respectively. While the standard deviation for industrial properties is only 1.1% less than that for retail properties, the support of its returns distribution is substantially smaller, which indicates that industrial properties have fewer extreme years than retail properties.

*** Table 1 ***

We begin our assessment of the regional returns by examining the regionally disaggregated means and standard deviations. We present these in Table 2. For each type of property, the mean returns for the regions are grouped tightly around the mean return for that propelty type. To illustrate this, consider the spread of the mean rates of return for retail property, by region. The standard deviation of mean returns for the 13 regions around the mean for retail properties is just 1.3%, while the standards deviation for the individual regional series ale all around 18%. Hence, most of the variation is time based. As a corollary, regional differences do not explain the variation rates of return to retail properties. In fact, we cannot reject the null hypothesis of homogeneity across regions.9 We obtain analogous results for the other two property types.

Anselin (1988) argues that spatial effects may be more complicated than the simple level differences just examined. He develops a range of econometric models for estimating regressions with more general forms of spatial dependence. These models have been used successfully in a several of recent articles (Pace and Gilley 1997, Pace *et al.* 1998) to investigate spatial dependence in property pnces.

*** Table 2 ***

We take a quick look at spatial dependence by calculating a simple regional contrast. The contrast is the difference of the mean return for a region from the mean return for the relevant property type, divided by the standard deviation of returns for the region. Dividing by the standard deviation is a crude adjustment for relative regionai risk.

This measure indicates a limited degree of regional dependence. For retail properties, the Northwest and Yorkshire and Humberside regions form a pocket of low returns. The Southwest, West Midland and Wales form an area of high returns for of fice properties, while Central London, Suburban London and the Southeast region form an area of low returns. We discern no spatial dependence for industrial properties.

The last column of Table 2 contains the Phillips-Perron t-test statistics for unit roots in the real returns for each region. For every return series, we can reject the null hypothesis of a unit root. However, we cannot reject the null hypothesis for the inflation time series.

These test results cast doubt on the findings in Harbert's (1998) cointegration study. She also

bases her study on the Hillier Parker data set, but uses the semi-annual rather than the annual series. Harbert tests for cointegration among the *nominal* regional reelrns by conducting airwise tests of cointegration between the London region and each of the other regions. Her zsllllts show a demonstrable degree of regional cointegration in the retail and of fice sectors, t little cointegration for the industrial sector. These results are based on the nonstationarity ; the nominal rehurns. Our test results suggest that the nominal retums are nonstationary nply because inflation is nonstationary. Viewed in this light, Harbert's results are related nore closely to the regional generation or transmission of inflation than with the market undamentals goveming regional property returns.

since our results show that all the real, regional return series are stationary, our next step is to letermine which series display persistence. We do this in three ways. First, we regress the ^+urn for each region on its lagged values. We begin by estimating an AR(5) and apply a sackward sequential Wald test strategy to determine the maximum AR order consistent with he data. We record the results of this procedure in the second column of Table 3. The arameter estimates for the final autoregression are given in the appendix in Table Al . As)ur second method for determining persistence, we perforrn a Box-Jenkins order selection for :ach univariate reaurns series. The AR and MA orders determined this way are given in rolumns 3 and 4 of Table 3. Our third method is to fit each Box-Jenkins model to verify the rder section of the second method. The fitted AR and MA orders are presented in columns 5 ind 6 of Table 3.

rhe results we obtain from these identification methods are similar. The AR order selection 7rocedure indicated that 8 of the 13 retail return series are autoregressive. Most of the wutoregressive series are AR(4), which implies a long term business cycle in the returns. The Box-Jenkins order selection and fit confirm these findings and reveal that there is no latent \{A component,'_ except for shops in central London. Scotland is the only region for which we obtain conflicting results. In our estimation below we take it to be AR(2). The returns on of fice properties are not persistent for most regions of the United Kingdom, with the exception of London, the Southeast and Scotland (7 of 15 regions). In general, these areas have high order autoregressive returns, AR(3) or higher, and there is little evidence of moving average errors. However, the Holbom/Marylebone area stands out among the London areas as different. It is best modelled as an ARMA(1,3) or ARMA(0,4). The evidence concerning the persistence of the returns to industrial properties is weak. The AR order selection procedure suggests that none of the regions have persistent retulns. The Box-Jenkins identification and fit indicate that London and the southern regions of the U.K. have an AR(4) representation. This is an odd result, since both of these methods are based on regression estimators. A closer look at the estimation routines reveals a difference in how they condition the estimates on the initial observations. The autoregression places greater weight on the initial observations which, when coupled with the large changes in reaurns over the first few observations, tends to cloud the results. In the analysis below, we take the returns in the south of England to be persistent, but recognise that caution is needed in using our results for this sector.

7.0 **Common Features Tests**

We can now proceed with the tests for serial correlation common features among the persistent series for each property type. In principle, these tests can be derived using general VAR representation containing all the relevant series and the number dimension of the cofeature space can be derived as described in Section 3. However, we have a large number of series and a small number of observations, so we proceed gingerly, beginning with a pairwise analysis of relevant reaurns series.

In Table 4, we present the Tiao-Tsay SCM tests for the persistent retail property returns series. The paired regions are indicated in columns one and two. Column 3 records the moving average order of the SCM at which a cofeature vector is detected. In almost all cases, an SCM(0,0) is the appropriate model. This indicates that most of the return series pairs have synchronous hIlpulse responses. We expect this in a financial model where arbitrage is driving the result, but not in a regional adjustment model. The common features tests are recorded hl columns 4 through 8. A single cofeature vector binds most of the regional pairs, except those with Scotland. This indicates that there is a single common cycle underlying each regional pair. Since this result is shared among the mutual regional pairs, it suggests that there is a single common cycle for the retail property sector.

In the last column in the Table 4, we give the eigenvector corresponding to the staustically insignificant canonical correlation. (i.e., the statistically significant C statistic). This eigenvector is a consistent (but not unique) estimate of the cofeature vector. It is normalised to identify it. The normalisation forces the first region in the pair to have a coefficient of unity. In terms of our simple financial model, the coefficients in Table (4) correspond to -_12 = -u11/fi12 - the sensitivity of region I retums to the common risk factor relative to region 2 returns. In broad terms, the estimates have three features. (I) London is relatively more sensitive to the common cycle than are the regions. (2) For many regional pairs, the coefficient is close to unity, indicating equal sensitivity. (3) There is a tendency for the coefficient to decline with the distance between the regions, indicating a potential autoregressive dependence between the regions.

The relationship between Scotland and the other regions is more complex. In three of the seven pairings with Scotland (SW, NW, YH), the tests indicate a SCM (0,2) and the presence of a second cofeature. In these pairings, there is no common trend between the regions. Instead, there is a complex, two year, dynamic adjustment process linking the regions.

** Table 4 (parts I and 2) ***

Our results for of fice properties are given in Table 5. The results parallel those for retail properties. Most of the regional pairs are SCM (0,0), although the London areas and the Southeast lean toward a SCM (0,1). That is, the intra-London returns adjustment process appears to have a short term memory of past pricing errors. The tests reveal that all the regional pairs are linked by a single cofeature, except Suburban London versus Scotland, where there are two cofeatures. Again, these findings suggest a dominant national cycle. The most pronounced difference between the of fice and retail properties is in the estimated magnitudes of the coefficients of the cofeature vectors. They indicate that the London areas are more sensitive to the national common cycle than are the other regions. In addition, the coefficients clearly are related to distance. The coefficients increase markedly in size with the distance from London. This implies that the 'national cycle' is really a London cycle and that the other regions adjust to the shifts in the London returns.

*** Table 5 ***

Table 6 contains the regional common factor tests for industrial properties. These results are similar to those for the other two sectors. For all pairs of regions, the tests indicate a SCM(0,0) model. The tests also indicate that each pair of regions shares a single common cycle. The Southeast region is the exception. This region is related to the Southwest, East Midlands auld Scotland regions by two cofeatures. In other words, these pairings have no common cycle. However, the estimated cofeature vectors tend to have one large and one small coefficient, which suggests that there is a Southeast factor and a national factor in play.

*** Table 6 ***

We are now in a position to perform common factor tests using all the regions for each type of property. On balance, the preceding evidence suggests that we may restrict ourselves to SCM(0,0) models and that we may limit the instrument set to the fourth or highest lag of the regional return series as indicated in Table (3). The latter restriction is necessary to conserve

degrees of freedom. Based on our results so far, we expect to find at least one common cycle

r each sector and, perhaps, additional common cycles for the retall and of fice sectors. Our t results are given in Table 7.

*** Table 7 ***

Tests confirm that a single common cycle is the basis of the retums in the retail and dustrial sectors. If we raise the significance level from 5% to 7%, there is a second ammon cycle for the retail sector. The returns to the of fice sector have three common Fcles. The pairwise tests show that the returns in the London markets have a more elaborate fa generating process. Therefore, we are interested in whether our common cycle results ~Id up when the analysis is restricted to the London region. The lower right hand panel of)le 7 contains the relevant results. The test clearly shows that the London region also has ree common cycles.

4 **Common Features Models**

this section, we focus on estimating the parameters of the common features models

icated by the tests in the preceding section. We consider here only the SCM (0,0) model. der the null hypothesis, we can transform the VAR representation (2) into the following eudo-structural form

[I rX'] [_

matrix on the left hand side of the equation is the full rank transformation matnx that Ids (10) by premultiplication and using the restrictions (3). The top row of the nsformation matrix is the transpose of the matrix of cofeature vectors, sc'. We refer to the mns of a' as the common cycle vectors. Since we can determine only the basis of the cofeature space, o is rotated so that rt' = [15, a'] This singles out the first s return series as dependent on the last N-s series, but we could equally well have chosen any rotation of the matnx to identify the system. The matrixes A, are the lower ((N-s)xN) dimensional submatrices of the VAR coefficient matnces Aj. The upper (sxN) dimensional sub-matrices of Ai equal - ct'A, .

Vahid and Engle (1993b) show that all SCM(0,q) models can be embedded in a VAR(p). The psuedo-structural forms for these model all resemble (10). However, for q>l, the restrictions on the VAR coefficient matrices are nonlinear and become increasingly complex. Hence, the VAR matnces Aj are complicated nonlinear ftmctions of the estimation parameters.

We estimate a SCM(0, 0) model for each property sector. Initially, we used the fourth or highest order lags of all the return series in the VAR specification of the models. This is the same specification employed in the SCM tests in Table 7. However, all the estimated models exhibited multicollinearity, together with the attendant inflation of the standard errors. To remedy the problem, we estimated simpler models. The final models for each sector is the outcome of a specification search. All the estimates a derived by full information maximum likelihood estimation (FIML) of (10).

We present our estimates for the retail sector in Table 8. Despite the marginal significance of the second common cycle in the common feature test, we originally based our estimates on the assumption two common cycles (6 cofeatures). We choose Central London and Scotland as the fluctuating sectors. However, we did not find a single statistically significant element for the second common cycle vector. Therefore, we drop the second common cycle from the estimation, but continue to carry Scotland as an independent fluctuating sector.

*** Table 8***

The remaining common cycle vector has statistically significant coefficients for the Yorkshire and Humberside, Northwest, Wales and Southwest (at 6%) regions. The parameter estimates indicate that roughly 50% of the Central London cycle is transferred to these regions. The coefficients for the EM and EA regions are statistically insignificant. This is problematlc. it suggests that Central Londoll does not impart a cycle to these regions. Yet, the bivariate tests reported in Table 4 indicate that it does.

The two estimators differ markedly in their VAR specifications. Our bivariate estimator uses a larger set of instruments than does our FIML estimates. This suggests that we should expand our model for VAR Central London, despite the fact that multicollinearity will render individual coefficients statistically insignificant.

The constant terms are the next set of parameter estimates in Table 8. These terms measure the difference between the long run return for the region and the long run return passed on from the returns in Central London. A statistically insignificant coefficient implies that there is no difference in the long run returns. All of the regional constant terms are statistically insignificant. This suggests that there is a single risk adjusted long run rate of return for all the regions in the analysis.

*** Table 9 ***

The returns for Central London depend on the fourth lags of the returns to Scotland, East Anglia and Central London. The Scotland and Central London effects are both negative and statistically significant. The estimates show that a 1% increase in the rate of return in Central London today will reduce the rate of return four years hence by 0.38%. A similar increase in Scotland will reduce the Central London rate of retum by 0.30% in four years. The coefficient for East Anglia is 0.250. The Wald test for this coefficient indicates that it is statistically insignificant, but the likelihood ratio test indicates that it is statistically significant. This is another manifestation of the multicollinearity. The point estimate implies

that a 1% increase in the rate of return in East Anglia induces a 0.25% increase in the Central London rate of retum in 4 years. The constant tenn equals 15. 1% and is statistically significant.

The model for Scotland is a simple AR(2), as we can not substantiate any significant crosseffects from the other regions. That is, Scotland affects other regions, but it is not affected by other regions.

Table 9 contains our results for the of fice sector. The common features tests indicate that this sector has three common cycles. The tests also suggest that these are London cycles. Therefore, we use three areas of London: the City Fringe, the West End and Central London as the primary cyclic areas. This leaves Scotland, the Southeast, Suburban London and Holborn/Marylebone as the areas inheriting the cycles.

From the coefficient estimates, we observe that the West End common cycle has the most pervasive effect on the 'determined' areas. Fluctuations in the retums for West End properties have a statistically significant effect on the Southeast (0.74), Suburban London (0.73) and Holborn/Marylebone (0.92) areas. The City Fringe common cycle affects the returns in Scotland negatively (-0.44) and the results in Holborn/Marylebone positively (0.55). These affects are also statistically significant. The third common cycle transmits fluctuations in the returns for Central City properties to properties in the Holborn/Marylebone area. This coefficient equals -0.20, but it is statistically insignificant. This cast some doubt on the existence of the third common cycle,

Three of the four constant terms in the structural model are statistically insignificault. The fourth constant is for the Southeast region. It equals 0.079. This means that the drih for the Southeast region is 7.9% greater than can be accounted for by the transmission of the London cycles. We note that the constant terms in the West End and Central City equations are statistically insignificant. Hence, its is principally the Fringe City drift that is being transmitted to the other regions.

The returns to Fringe City of fice properties are separable from the returns in the other areas. hese returns have a univanate autoregression with coefEcient at lags I and 4. The zefficients show that a 1% increase in the rate of return today, adds 0.43% to the return in 1e year and subtracts 0. 16% in four years. This implies a cumulative impulse response hultiplier of 1.37.

The returns equation for the West End also contain AR(I) and AR(4) terms. The values of ese terms are -0.49 and 1.59, respectively. In addition, the returns in the West End respond rongly to the rates of return in Scotland (0.51) and Holbom/Marylebone (-1.97). All of ese coefficients are statistically significant.

The returns in the City Centre are strongly first order autoregressive. 80% of every shock to be rate of return is transmitted to the next period. The AR(4) tertn, which was significant in e other areas, is statistically insignificant here. Curiously, the higher order effects are lated to the rate of return in Scotland. A 1% increase in the rate of return to of fice roperties in Scotland decreases the rate of retum to City Center of fices by 0.27% two years Iter and increases them by 0.12% four years later.

tur last set of results is for industrial properties. These results are in Table 10. The common Xature test for these properties discloses one common cycle, which we identify with the outheast region. The coefficients of the common cycle vector show that a significant mount of the cyclicality of the Southeast region is passed on to the Southwest (1.00), East nglia (1.06) and East Midlands (0.71) regions. The coefficient for Scotland is small, egative and wholly statistically insignificant. Thus, industrial property retums in Scotland ppear to be disconnected from the other areas.

*** Table 10 ***

The constant terms for the dependent series are all statistically insignificant. Like the retail sector, industrial sector appears to have a single risk adjusted long nun rate of return for all the regions.

The rates of return for the Southeast region are an autoregressive AR(2) process plus cross etfects for the returns Southwest region at lags 2 and 4. All of the coefficients are statistically significant. The AR coefficients are 0.20 and 0.68. This indicates that approximately 88% of shock to the return to Southeast industrial properties is carried forward. This is mitigated by the cross-effect with the Southwest region. The lag-2 coefficient for the Southwest region is -0.94 and the lag-4 coefficient is -0.34. Combining values of these coefficients with the unit coefficient of the Southwest region in the cofeature vector, gives a cumulative impulse response multiplier of about 0.72.

9.0 Conclusion

Our objective in this paper was to determine whether common cycles exist among the regional rates of return for U.K. commercial properties. Our tests establish that the retail and industrial sectors each have one common regional cycle. The of fice sector appears to have three common cycles and these cycles. In addition, our common features tests suggest that transmissiou of these commou cycles is rapid enough that we can not reject the hypothesis that synchronous common cycles across the regions in a yearly period. However, further research is needed into this issue. In addition to the common features tests, we estimate common features models for each sector. These models tend to confirtn the tests.

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*** Table Al 1**

Notes

' See Vahid and Engle (1993) for the movhlg average representation. 2 This point is made by Ericsson in his comments on Engle and Kozicki (1993). 3Tiao and Tsay (1985) show that these are the eigenvalues of the matrix

T I T T _l T

G(m,q)= Ertrt' E rtZm,t>_l S Zm,t-q-lZm,t-q-l E Zmt>-lrt

t=m+l t=m+l t=m+l t=m+l

= rfr) (m, q + I)r(Z) (m, q + I)

Obviously, r(Z)(m, q) is the OLS coefficient matrix from the regression of r. on Zm, t q l, which measures the dependence of r, on past information. r r)(m, q) is the coefficient matrix from the reverse regression, which measure the dependence of Z,n, t q.l on the leading information in r,. The product of these two coefficient matrices is a measure of the leading and lagging codependence of the primary time series.

4 The variable v(Z)(i) = ej' Zm, ,,q.l where, in this case, e; is the ith ordered eigenvector of the matrix r(Z)(m, q+l)7~(')(m, q+l) rather than rr)(m, q+l)r(Z)(m, q+l).

5 Many types of common features do not involve serial correlation. One simple example is a non-forecastable event that affects market returns. This is a pricing factor, a common feature, but it is not a serial correlation common feature.

6 An example of this is Dkl/5kj = 07+t)jk, k= I ,. . .,K, where tijk are errors distributed independently from the systematic risk factors.

7 In stating this, we are making the usual assumption that the number of risk factors is much smaller than the number of retums.

8 The rates of return in this data set are valuation based.

9 We use a standard %2 homogeneity test.

'_ One can reach the same conclusion from the Durbin-Watson statistics for the autoregressions in Table Al.