Forecasting models of retail rents

Brooks and Tsolacos, 2000. The definitive, peer-reviewed and edited version of this article is published in Environment and Planning A, 32, 10, 1825-1839, 2000, DOI: 10.1068/a3332

Forecasting models of retail rents

Chris Brooks (corresponding author)

ISMA Centre, Department of Economics, University of Reading, Whiteknights, Reading, RG6 6BA

and

Sotiris Tsolacos

Jones Lang LaSalle, 22 Hanover Square, London, W1A 2BN

Forecasting models of retail rents

Abstract. This study models retail rents in the UK using a vector autoregressive and time series models. Two retail rent series are used, compiled by LaSalle Investment Management and CB Hillier Parker, and the emphasis is on forecasting. The results suggest that the use of the vector autoregression and time series models in this study can pick up important features of the data that are useful for forecasting purposes. The relative forecasting performance of the models appears to be subject to the length of the forecast time horizon. The results also show that the variables which were appropriate for inclusion in the vector autoregression systems differ between the two rents series, suggesting that the structure of optimal models for predicting retail rents could be specific to the rent index used. *Ex ante* forecasts from our time series suggest that both LaSalle Investment Management and CB Hillier Parker real retail rents will exhibit an annual growth rate above their long-term mean.

1. Introduction

Retail properties typically constitute a significant part of the property component of institutional portfolios. Direct institutional investment in the retail market comprises high street shops, shopping centres, retail warehouses and other retail outlets. According to Jones Lang LaSalle, investment in shopping centres alone increased from about £900 million in 1995 to over £3 billion in 1998. Retail development is also a significant part of total commercial building construction. The value of new orders obtained by contractors for shops was 31% of the total private commercial in 1998. The importance of the retail sector in institutional portfolios and the property development industry warrants research on the profitability of the retail built environment. Empirical work to uncover the drivers of the performance of the retail property market is essential to improve the quality of portfolio and development decisions.

Institutional investors, banks and property developers also require that the various techniques used to estimate the future performance of retail property investment and development take explicitly into account forecasts of rental growth both at the aggregate and the more local level of analysis. More sophisticated techniques are now in demand since they may potentially allow a better understanding of the sources of past changes in the market environment and enable these changes to be built into the rent forecasts. Therefore, given that rent forecasts are an inherent element in the process of making investment decisions and building development plans in the retail property market, developers and investors face two tasks: first, to become familiar with the structure of alternative forecasting models so that they can explain how the forecast output is produced; and second, to examine whether forecasts from other modelling techniques can improve upon forecasts from existing either naïve or more complex approaches. These tasks highlight the need for comparative work that evaluates the forecasting adequacy of different methodologies. Existing published work on retail rent forecasting has been too sparse to fully satisfy this requirement. Two studies have attempted to rectify this omission in the UK. McGough and Tsolacos (1995) used time-series techniques to forecast rents one step ahead and Tsolacos (1995) constructed a single equation model to predict quarterly retail rents four quarters ahead.

The present study focuses on the predictability of retail rents in the UK and furthers the existing limited work on the subject. The principal objective is to assess the capability of alternative methodologies to forecast retail rents in the short-run. A number of economic and non-economic factors have had an effect on trends in the retail sector and the retail property market in the last two to three decades. Non-economic factors include the changing demographics (Lachman and Brett, 1996) and dynamics of retail location (Eppli and Shilling, 1996), the re-configuration of the shape and composition of traditional shopping centres, the recent advent of e-commerce and, in the UK, the shifting emphasis in Planning Policy Guidance 6 (PPG6) in the last 15 years. It can be argued that the effect of these social and institutional factors on the retail property market (prices and volume and type of development) is gradual and of a more long-term nature. PPG6 could be the exception, but analysts agree that the effects of the changing guidelines in 1988 and 1993 on the retail market spanned several years. The first methodology deployed in this paper aims to capture the more short-term effects of fluctuating economic conditions and new retail construction on retail rents. It therefore attempts to explain and forecast retail rent movements at the aggregate level solely on the basis of the economic drivers of the demand for retail properties, that have received support in the relevant literature, and the supply of new retail space. The methodology used to accomplish this task is an unrestricted vector autoregression system. The principal use of vector autoregression systems in applied work is the production of short-term forecasts.

Retail rent forecasts are also produced by three other methodologies: an autoregressive procedure, a long-term mean model and a random walk model. These procedures are based purely on past rent behaviour and therefore they do not take into account external influences. Smoothing arising from valuations in the construction of property rent indices and the slow adjustments in the (retail) property market, following demand or supply shocks, necessitate an examination of the hypothesis that past rent movements are an important source of information for future rent movements. The autoregressive procedure is but one component of the VAR system, and it is therefore a simpler methodology than the latter. The long-term mean and random walk models represent more naïve methods of forecasting. Forecasts from these methodologies provide a useful benchmark against which an analyst can judge the output of other approaches. The evaluation of the performance of the alternative forecasting models is made on the basis of the output of a number of commonly used criteria.

Two rent series are used in this forecasting investigation: the LaSalle Investment Management rent index and the CB Hillier Parker index. The objective of this decision is to examine the sensitivity of the forecast output to the use of different retail rent time-series. If such differences exist, it can be argued that forecasts of retail rents are subject to another influence, that of the particular series used.

The remainder of the paper is organised to four sections. Section two summarises the main influences on retail rents which are relevant for the model-building process. Section three outlines the methodology, explains the forecast evaluation process and describes the data. Section four reports the results of the empirical estimates and the forecasts. The conclusions are set out and the implications of the findings are discussed in section five.

2 Influences on retail rents

Existing published econometric work has identified factors responsible for the variation in retail rents through time and across retail centres. In the UK literature, models of retail rents incorporate the influences of economic factors at the national and regional levels. The majority of studies use single regression equations that represent the reduced form of a structural demand-supply model. The implicit theoretical assumption in these models is that conditions in the business of retailing and the retailers' profitability will determine demand for retail space and induce variation in retail rents. Variables that proxy the strength of the demand for retail space relate proportionately to the the variation in retail rents. The supply of retail space is also expected to have an influence on retail rents. New construction and retail space supply from the existing building stock relate inversely to rent growth since excessive new construction and supply of pre-existing space tend to dampen growth in rents whereas retail space shortages (new or from existing buildings) tend to sustain rent increases.

Authors are therefore in search of variables that can effectively convey demand - supply effects on retail rents (see Fraser, 1993; RICS, 1994 and Tsolacos, 1995). Alternative economic time-series are often considered since there are no strong *a priori* grounds as to which indicator or series best represents demand in the retail market. On the supply side, the choice of variables at the more aggregate level in the UK is very limited and the most consistent new construction series appear to be those compiled by the Department of the Environment, Transport and the Regions.

Hillier Parker (1984, 1985, 1987) modelled retail rents as a function of retail profits and disposable income whereas Hetherington (1988) as a function of retail sales. These demand-orientated models did not exhibit the same degree of success in explaining rents in retail sub-markets across the country. This was attributable to the particular characteristics of the markets considered and the differences in the data available for each of these markets. The study of RICS (1994) estimated national and regional models of retail rents and demonstrated the importance of consumer spending, interest rates (as demand side variables) and new retail orders (a supply side series). Tsolacos (1995) also found evidence that consumer expenditure is important in determining retail rents. In addition, changes in the gross domestic product appeared significant. Another finding of the latter two studies is that the contemporaneous variation in retail rents relates strongly to the variation in rents in the recent past.

The US literature follows a different path of research. Retail rent variation is largely examined at the 'micro' level (shopping centres) and studies investigate the relevance of both economic determinants and other non-economic factors. Benjamin *et al* (1990) investigated the trade off between base and percentage retail rent and found that the base rent responds to the variation in threshold sales. Sirmans and Guidry (1993) estimated a hedonic model to conclude that rents across shopping centres are influenced by the customer drawing power (proxied by total area, age and type of anchor tenant), location, building configuration and general economic conditions. With the means of a survey of professionals' opinions, Ownbey *et al* (1994) examined the impact of different types of location variables on gross rents in neighbourhood shopping centres. More recently, Eppli *et al* (1998) highlighted the importance of unexpected sales in explaining changes in real estate returns (through the effect on retail rents) in localised retail markets. The estimation of a simultaneous demand-supply model of the retail market by Benjamin *et al* (1998) showed that almost all variation in contemporaneous retail returns can be explained by retail returns lagged a year and the vacancy rate.

Therefore, existing empirical analysis has provided insight into the underlying economic and other factors that help predict the variation in retail rents. UK and US studies have found empirical support for key macroeconomic aggregates that include consumer spending, retail sales, gross domestic product and disposable income. Furthermore, UK research has allowed for supply side effects on retail rents with the inclusion of the new retail orders series that measures the level of new retail development starts. Although the new retail orders series does not refer to the final completion of retail structures but to the time that the project starts, it represents a consistent series through time that covers the UK as a whole. As a result, it is considered a good indicator of the forthcoming supply of new retail space at the aggregate level, despite concerns about the quality of the series that some authors have expressed. Time series to allow for the effects of the other components of supply, that originate in existing buildings, at the aggregate level do not exist.

A review of the empirical studies also points to the importance of past retail rents on their current values (therefore the variation in retail rents is partially generated by an autoregressive process). This could be the result of the way that the rental data series are constructed. Valuation processes contain an element of smoothing that make the correlation of adjacent rent observations stronger. The importance of past rents may also indicate the influence of missing variables. The shortage of good quality construction data at the more aggregate level of analysis is a likely source for this type of mis-specification. Alternatively, slow adjustments in the market following demand and supply shocks can explain this finding.

3. Methodology, forecast evaluation and data

3.1 Methodology and models

This study adopts four methodologies to forecast retail rents. The past cyclical behaviour of rents and their long-term trend lay the foundations for three of these methodologies, the autoregressive process (AR), the long-term mean and the random walk model. The fourth approach, the vector autoregression (VAR) system, is intended to incorporate, in addition to the past variation in rents, the effect of economic and new construction variables that have received empirical support in the literature. These variables are consumer expenditure, retail sales, disposable income, gross domestic product and new retail orders.

Initially all variables used in this study are tested for stationarity (so that the mean, variance and autocovariances are independent of time), that is, the variables are tested for unit roots. The main statistical reason for this is that stationary series are required by the autoregressive model and for valid application of and inference under the least squares method in vector autoregressions. The presence or otherwise of a unit root in the series (implying that a variable is not stationary) is examined with the application of Dickey Fuller tests (Dickey and Fuller, 1979, 1981). Since many economic series are non-stationary in levels, a series of changes, or first differences may be constructed to ensure stationarity. The fact that stationary aggregates are included in the analysis implies that only the short-term movements of retail rents are modelled and forecast. Any long-run relationships between rents and the selected variables are not taken into account in this forecasting exercise.

Subsequently, Granger causality tests (Granger, 1969) are applied to examine whether the relationships between retail rents and the variables conform to theoretical intuition. Granger causality tests are conducted to establish patterns of causality (or precedence) between retail rents and the selected aggregates that is whether a movement in these variables precedes that in retail rents. In the context of the present study, all variables are expected to drive (precede) retail rent movements. The Granger causality tests will determine which variables are to be included in the vector autoregression system. If a variable does not have a significant impact on rents under this test, it is excluded from the system. Based on the results of these tests, a vector autoregression system is constructed and estimated for each of the rent indices. These four methodologies are described in more detail below:

Unrestricted VAR model

The reduced form vector autoregression (VAR) model is a generalisation of an autoregressive model. Within a VAR model, the variation in a given variable is explained by its own lags and the lags of other variables which are related *a priori* to the former. Using matrix notation, the VAR system can be written as:

$$\mathbf{Y_t} = \mathbf{B_0} + \mathbf{B_1}\mathbf{Y_{t-1}} + \ldots\ \mathbf{B_m}\mathbf{Y_{t-m}} + \mathbf{U_t} \qquad (1)$$

where $\mathbf{Y_t}$ is an $n \times 1$ vector (list) of variables. Therefore in the VAR system there are n equations, and m represents the maximum number of lags of each variable that enters the equations of the system. The vector $\mathbf{B_0}$ is a $n \times 1$ matrix of constants and the $\mathbf{B_1}$, ...$\mathbf{B_m}$ terms are sets of coefficients on the lagged variables. The variables included in $\mathbf{Y_t}$ (on the left hand side) are explained by the past values of the same variables on the right hand side, and there is an $n \times 1$ vector of error terms ($\mathbf{U_t}$) which are assumed to be independent of the $\mathbf{Y}$s, but they can be contemporaneously correlated. The coefficient matrices can be efficiently estimated equation by equation with ordinary least squares and are treated as fixed when the VAR model is estimated. In the estimation of a VAR model, statistical tests are used to decide upon the appropriate number of lags for each equation. In this study, the multivariate generalisations of the Akaike information criterion (AIC) and the Schwarz-Bayesian information criterion (SBIC) are used to determine the lag length of the VAR system. These criteria effectively impose a penalty on the lags that do not carry explanatory power and trade off a reduction in the sum of squares of the residuals for a more parsimonious model.

VAR models have proved very useful devices in macroeconomics for short-term forecasting. In property research, authors have mainly used VAR systems to examine the dynamic response of property market series to economic and financial variables (Brooks and Tsolacos 1999, Kling and McCue 1987, 1994, McGough and Tsolacos, 1999). Property researchers have not explored the potential of this forecasting procedure with the notable exception of the study of McGough and Tsolacos (1994) who used VARs to predict quarterly office rents in the UK.

The variables to be included in the vector $\mathbf{Y_t}$ (and the vectors of lags $\mathbf{Y_{t-1},...,Y_{t-m}}$) of the VAR model will be determined by the Granger causality tests. In addition, the vector incorporates the effect of the past variation in retail rents. This is in accordance with the findings of previous research both in the US and the UK that that past values of retail rents are important in explaining their current levels.

The VAR methodology has certain advantages. It avoids the often arbitrary choice of identifying restrictions of structural econometric models. The simultaneity problem of multi-equation structural models is not an issue with VARs, since there are no concerns regarding which variables should be treated as exogenous or endogenous. Overall, VARs are more flexible than single estimation techniques and simpler to specify and to work with than simultaneous equation models. VARs have received attention due to the belief that unrestricted VARs would perform better in forecasting than structural multiple equation models (Litterman, 1979 and Sims, 1980). On the other hand, VARs have also been the subject of criticism. This mainly relates to the interpretation of variance decomposition and impulse response functions that can be carried out within a VAR to trace the effect of one variable on another in the system through time (see for example Runkle, 1987 and Greene, 1993). VARs are also somewhat more atheoretical, and their individual coefficients more difficult to interpret, than is the case for simultaneous structural models.

Autoregressive (AR) model

The purely autoregressive time series model is described by equation (2):

$$(Y_t-\mu) = a_1(Y_{t-1}-\mu) + \ldots a_m(Y_{t-m}-\mu) + u_t \qquad (2)$$

where Y_t is the tth observation on the dependent variable, μ is the mean of the series, and u_t is the error term with zero mean and constant variance. Within an autoregressive representation, the value of the series at time t is expressed in terms of lagged values of the series and a current random shock. The value of Y at time t is some proportion a_1, a_2, … a_m, of its value at time t-1, t-2, …, t-m respectively plus a random shock at time t. The Akaike and Schwarz criteria are used to determine the appropriate number of lags in equation (2).

Long-term mean model

The long-term mean is simply the arithmetic mean of the rent series over the sample period considered. The value of the arithmetic mean over a given sample period provides the basis for the forecasts, the presumption behind this model being that the change in retail rents has some long term average value.

Random walk model

The assumption in a random walk model is that the rent series wanders up and down randomly with no tendency to revert to any particular trend or point**.** The levels of rents, following a shock that lowers or increases their value are assumed by this model to show no tendency to return to a particular mean level. Thus a shock has permanent effects on rents. This model resembles an

AR(1) model with a unit coefficient on the lagged term. The random walk model is given by equation (3):

$$Y_t = Y_{t-1} + e_t \qquad (3)$$

where e_t is a random error.

The above models are estimated with quarterly data. The full sample period is 1977 quarter two to 1999 quarter one.

3.2 Forecast evaluation

All four approaches are used to make eight out of sample (dynamic) quarterly forecasts. These forecasts are made recursively and the start date is 1988 quarter one. This means that the VAR and AR models are fitted to the rent series for the period 1977 quarter two to 1987 quarter four and forecasts are made for eight quarters ahead 1988 quarter one to 1989 quarter four. Similarly the long-term average of the rent series (estimated over the sub-sample 1977 quarter two to 1987 quarter four) is used for the eight-quarter forecast. The forecast of the random walk model for the period 1988 quarter one to 1989 quarter four is the value at 1987 quarter four. Subsequently, the models are estimated up to 1988 quarter one and an eight-quarter forecast (1988 quarter two to 1990 quarter one) is again computed. This procedure continues until the forecast sample period is exhausted (the last forecast is made in 1997 quarter one for the period 1997 quarter two to 1999 quarter one). In this way forty-four one-quarter forecasts, forty four two-quarter forecasts and so forth are calculated.

The forty-four one-quarter forecasts are compared with the realised data for each of the four methodologies. This is repeated for the two-quarter, three-quarter, …. and eight quarter ahead computed values. This comparison reveals how closely rent predictions track the corresponding historical data of rent changes over the different lengths of the forecast period (one to eight quarters. This performance is assessed on the basis of the most commonly used forecast evaluation criteria and quantitative measures: the mean forecast error (MFE), the mean squared forecast error (MSFE) and the percentage of correct sign predictions. These criteria are deemed sufficient to identify the best performing models. A good forecasting model should have a zero mean so that it over- and under-predicts roughly the same number of times, thus leading to a small average forecast error (MFE). A model with a large positive (negative) MFE would indicate a model which consistently under- (over-)predicts. Thus MFE can give a broad indication of whether a given model produces biased forecasts. However, the MFE measure can conceal large forecast errors since its computed values are influenced by large positive and negative errors that cancel each other out producing low values for this measure. The MSFE, a more widely used criterion for evaluating forecasting performance, is a measure of the overall forecast accuracy of the model. It penalises large individual errors and provides a measure of the deviation of the forecasts from the actual time path of the variable being forecast. Lower MSFE values denote a better forecasting performance. Finally, the models' ability to predict the correct direction in rent changes (irrespective of their ability to correctly predict the size of the change) in each of the one- to eight-quarter forecasts is also assessed.

Ex ante forecasts of retail rents based on all methods are also made for eight quarters from the last available observation at the time of writing. Therefore, forecasts of real retail rents are made for the periods 1999 quarter two to 2001 quarter one.

3.3 Data

Two series of retail rents are employed in this investigation: the LaSalle Investment Management (LIM) index and the CB Hillier Parker (CBHP) index. The LIM series represents an overall retail rent index with a higher weight in standard shop units covering all geographical regions in Great Britain. It is based on the performance of a portfolio of actual properties. The type of properties included and its geographical composition represent the typical institutional portfolio. This index takes the value of 100 in 1977 quarter two. The CBHP index in Great Britain is also an overall index of retail rents covering all geographical regions. Rental values in this index apply to shops in the 100% trading position in a high street or a shopping centre measuring 20ft frontage by 60ft depth with 300 sq ft of storage or staff accommodation let on full repairing and insuring lease. Rental values also apply to units located in the adjacent trading areas of high streets and shopping centres. The index takes the value of 100 in 1977 quarter two. Both indices are converted into real retail rent indices (1977 quarter two = 100) using the all items retail price index. The LIM rent data were obtained from the quarterly UK Property Index publication of LaSalle Investment Management. The CBHP data and the retail price index were available from *Datastream International*.

The series used for consumer spending is total household expenditure (HEX) that covers all domestic expenditure on goods and services in Great Britain. The data are available in real terms. The gross domestic product (GDP) series is based on value added estimates. The series is available in constant terms. The retail sales (RS) series is the monthly retail sales estimates that cover retail trades (excluding motor trades) and it is a volume measure of retail sales. The personal disposable income (Yd) is the disposable income of the personal sector that consists mainly of households and individual residents in the UK together with unincorporated businesses, private trusts and life assurance and pension schemes. The series is also published in real terms. All these macroeconomic aggregates are available from the Office for National Statistics and were taken from *Datastream International*.

New retail orders (NRO) relate to contracts for new retail construction work placed with contractors by clients in the private sector. The value of this work is recorded in current prices in the period when foundation works are started on retail projects (such as shopping centres, retail parks and shop units) for eventual lease or sale. These figures are compiled quarterly by the Construction Directorate of the Department of the Environment, Transport and the Regions (DETR). The new retail orders series dates back to mid-1970s. At the beginning of 1990s, the DETR revised the series by excluding expenditure on infrastructure works related to retail projects. The revised net of infrastructure series is available from 1985 quarter one. However, it appears that the infrastructure element of the original series was not significant in relation to the total value of new retail orders and the series does not exhibit a jump before and after the first quarter of 1985. Therefore, data for this series prior to 1985 quarter one are also used as a proxy for new retail construction. The new retail orders data are converted into real terms (to produce a measure of the volume of new retail construction starts) using the all items retail price index. The source of the data is *Housing and Construction Statistics*, a publication of DETR.

4. Estimation results and forecasts

4.1 Results

The Dickey Fuller regressions are run with a constant and are augmented by the number of lags of the dependent variable that is necessary to minimise the Akaike's information criterion. The hypothesis of a unit root in all variables was clearly not rejected when augmented Dickey Fuller (ADF) tests are applied to the level of all variables. Subsequently, ADF tests are carried out on the first differences of all series. The results are reported in Table 1. All differenced series appear to be stationary at the five per cent level of significance except the rent series which are stationary at the ten per cent level. Therefore, all variables are included in the Granger causality tests, the VAR and AR specifications in first differences.

Table 1. Tests for stationarity

Variable	Computed ADF statistic
ΔLIM	-2.81
$\Delta CBHP$	-2.60
ΔHEX	-3.51
ΔRS	-3.97
ΔGDP	-4.01
ΔYd	-12.00
ΔNRO	-13.56

Critical values at 5%: -2.89 and at 10%: -2.58
Sample period: 77q3-99q1 for all variables except for ΔLIM (78q1-99q1) and $\Delta CBHP$ (78q4-99q1)

Table 2. Granger causality tests

Null hypothesis for causality	F-statistic	p value of F	Judgement - variable to be included in model?
	Results for ΔLIM		
ΔHEX Granger causes ΔLIM	3.53	0.01	Accepted
ΔLIM Granger causes ΔHEX	3.41	0.01	Accepted
ΔRS Granger causes $\Delta LIMR$	5.38	0.00	Accepted
ΔJLR Granger causes ΔRS	2.65	0.04	Accepted
ΔGDP Granger causes ΔLIM	2.77	0.03	Accepted
ΔLIM Granger causes ΔGDP	2.19	0.08	Accepted
ΔYd Granger causes ΔLIM	1.59	0.34	Rejected
ΔLIM Granger causes ΔYd	0.74	0.56	Rejected
ΔNRO Granger causes ΔLIM	1.38	0.25	Rejected
ΔLIM Granger causes ΔNRO	2.04	0.10	Accepted
	Results for $\Delta CBHP$		
ΔHEX Granger causes $\Delta CBHP$	1.33	0.27	Rejected
$\Delta CBHP$ Granger causes ΔHEX	3.43	0.01	Accepted
ΔRS Granger causes $\Delta CBHP$	2.22	0.07	Accepted
$\Delta CBHP$ Granger causes ΔRS	4.93	0.00	Accepted
ΔGDP Granger causes $\Delta CBHP$	2.47	0.05	Accepted
$\Delta CBHP$ Granger causes ΔGDP	2.01	0.10	Accepted
ΔYd Granger causes $\Delta CBHP$	1.63	0.18	Rejected
$\Delta CBHP$ Granger causes ΔYd	2.14	0.08	Accepted
ΔNRO Granger causes $\Delta CBHP$	2.49	0.05	Accepted
$\Delta CBHP$ Granger causes ΔNRO	1.32	0.27	Rejected

The number of lags used in the estimates is 4

The results of the Granger causality tests, shown in Table 2, establish similarities but also certain differences for the two rent series. There seems to be a two-way direction in the causality of *GDP* and retail sales and both rent series. On the other hand no causality is established between changes in disposable income and either of the rent series. Changes in total household expenditure Granger causes changes in LIM rents but not changes in CBHP rents. Conversely, changes in new retail orders Granger cause changes in CBHP rents but not changes in LIM rents. These differences in the results mainly reflect the disparities in the construction of the series. The different methods of constructing the rent indices give rise to distinct sensitivities to the same economic and construction variables. The contemporaneous correlation of these two indices (in first differences) is 0.84 over the period 1977 quarter three to 1999 quarter one suggesting that their pattern of variation is not indistinguishable.

Based on these results, the VAR model for LIM rents contains changes in total consumer expenditure, gross domestic product and retail sales and, of course, past values of rents. The VAR model for CBHP includes changes in the gross domestic product, retail sales and new retail orders. The lag lengths of both VARs and the univariate version for the AR models as they were determined by AIC and SBIC are given in Table 3.

Table 3. Lag lengths for the VAR and AR models

	VAR		AR	
Retail rents:	LIM	CBHP	LIM	CBHP
AIC	2	1	2	2
SBIC	1	1	2	2

These results show that even the Akaike's criterion selects relatively small lag lengths, probably because the number of observations is quite small. Clearly the appropriate AR models are of order 2 (AR(2)) for both rent series as the two criteria indicate. The selected VAR model for CBHP rents is of order one (VAR(1)). The two criteria, however, suggest a different order for the VAR model of LIM rents. As a result two VAR models are estimated: of orders 1 and 2 for LIM rent data. Therefore the CBHP VAR system comprises four equations - for retail rents, the gross domestic product, retail sale and the new retail orders - and in each equation just one lag of all variables is included. The LIM VAR system also contains four equations (retail rents, consumer expenditure, retail sales and the gross domestic product) but it is estimated with one and two lags of these variables.

The estimation output showed that the rent equation in the CBHP VAR model has a higher explanatory power than the LIM VARs. The R-bar squared of the former is 0.63. The LIM VAR(2) has a lower R-bar squared (0.36) and the LIM VAR(1) an R-bar squared of 0.13. However, if we consider that changes in rents are being modelled the performance of the VAR(2) models is reasonable since adjusted R squared values of less than 0.3 are not uncommon in the literature.

4.2 Ex post forecast evaluation

Table 4. Mean Forecast Errors for the Changes in Rents Series

	Steps Ahead							
Models	1	2	3	4	5	6	7	8
	Panel A: LaSalle Investment Management Rents Series							
VAR(1)	-1.141	-2.844	-3.908	-4.729	-5.407	-5.912	-6.158	-6.586
VAR(2)	-0.799	-1.556	-2.652	-3.388	-4.155	-4.663	-4.895	-5.505
AR(2)	-0.595	-0.960	-1.310	-1.563	-1.720	-1.819	-1.748	-1.876
Long term mean	-2.398	-3.137	-3.843	-4.573	-5.093	-5.520	-5.677	-6.049
Random walk	0.466	-0.246	-0.923	-1.625	-2.113	-2.505	-2.624	-2.955
	Panel B: CB Hillier Parker Rents Series							
VAR(1)	-1.447	-3.584	-5.458	-7.031	-8.445	-9.902	-11.146	-12.657
AR(2)	-1.845	-2.548	-2.534	-1.979	-1.642	-1.425	-1.204	-1.239
Long term mean	-3.725	-5.000	-6.036	-6.728	-7.280	-7.772	-8.050	-8.481
Random walk	1.126	-0.108	-1.102	-1.748	-2.254	-2.696	-2.920	-3.292

The evaluation of the forecasts obtained from the different methodologies is presented in Tables four to six. Table four reports the mean forecast error (MFE). As noted earlier, a good forecasting model should have a mean of zero. The first observation that can be made is that on average all mean errors are negative for all models and forecast horizons. This means that all models over-predict except for the one-quarter ahead forecast of CBHP using the random walk. This bias could be the result of trend influences that are omitted from the current analysis since stationary data are used or it could reflect non-economic influences during the forecast period. The continuous fall, however, in rents in the period 1990 to 1995, which constitutes much of the out of sample period, may explain to some extent this over-prediction. This arises from the fact that the majority of econometric models are relatively slow to adjust to changes in the underlying long-term behaviour of a series. It may also be that supply increases had greater effects during this period when retailers were struggling, than in the overall sample period. It could be that retailers benefited less than the growth in GDP at that time suggested, as people were indebted and seeking to save more to reduce indebtedness.

Of the two VAR models used for LIM rents, the VAR(2) model produces more accurate forecasts. This is not surprising given that the VAR(1) model of changes in LIM rents is a poor performer compared with the VAR(2) model. However, the forecasts produced by the random walk model appear to be the most successful when forecasts up to three quarters are considered. Then the AR model becomes the best performer. The same conclusion can be reached for CBHP rents but here the random walk model is superior to the AR(2) model for the first four quarter-ahead forecasts.

In the VAR forecasts, the values of the economic variables and new retail orders are predicted by the system itself. Alternatively, forecasts of these variables from other sources could be used. This would mean that at each quarter over the forecast evaluation period (1988 quarter one to 1997 quarter one), the most recent forecasts from an external source would be used for each of the economic variables and the new orders series. Given the long forecast evaluation period this is a rather laborious task. Alternative sources of information need to be consulted for the economic variables whereas the task becomes even more difficult for the new retail orders series as forecasts may not exist. Although this line of investigation is not pursued in the current paper, the use of external forecast values, in particular for the economic series, presents analysts with an alternative approach to forecast rents with VAR systems.

Table 5. Mean Squared Forecast Errors for the Changes in Rents Series

	Steps Ahead							
Models	1	2	3	4	5	6	7	8
	Panel A: LaSalle Investment Management Rents Series							
VAR(1)	111.30	112.92	112.59	106.86	106.00	108.91	114.13	115.88
VAR(2)	67.04	69.69	75.39	71.22	87.04	96.64	103.89	115.39
AR(2)	77.16	84.10	86.17	76.80	79.27	86.63	84.65	86.12
Long term mean	159.55	163.42	139.88	137.20	139.98	143.91	150.20	154.84
Random walk	138.16	132.86	162.95	178.34	184.43	196.55	202.22	198.42
	Panel B: CB Hillier Parker Rents Series							
VAR(1)	78.69	117.28	170.41	236.70	360.34	467.90	658.41	867.72
AR(1)	75.39	88.24	84.32	92.18	88.44	89.15	80.03	87.44
Long term mean	209.55	163.42	139.88	137.20	139.98	143.91	150.20	154.84
Random walk	198.16	132.86	123.71	149.78	132.94	148.79	149.62	158.13

The MFE criterion measures bias but this is only one component of the accuracy of the forecast. Table 5 shows the results based on the mean squared forecast error (MSFE), an overall accuracy measure. The computations of the MSFE for all eight time horizons in the case of CBHP show that the AR(2) model has the smallest MSFEs. The VAR model appears to be the second best performing methodology when forecasts up to two-quarters ahead are considered but as the forecast time horizon lengthens the performance of the VAR deteriorates. In the case of LIM retail rents, the VAR(2) model performs best up to four-quarters ahead but when longer forecasts are considered, the AR process appears to generate the most accurate forecasts. Overall, the long-term mean procedure outperforms the random walk model in the first two quarters of the forecast period in both series but this is reversed when the forecast period extends beyond four quarters. Therefore, based on the MSFE criterion, the use of the VAR(2) is the most appropriate model to forecast changes in LIM rents up to four quarters but then the AR(2) model performs better. This criterion also suggests that changes in CBHP rents are best forecast using a pure autoregressive model across all forecasting horizons.

From these estimates, it appears that rent changes have substantial memory for (at least) two periods. We can thus find useful information in predicting the rents in their own lags. The predictive capacity of the other aggregates within the VAR model is limited. There is some predictive ability for one period, which quickly disappears thereafter. It could be argued that this is to be expected since after one period, we do not have actual values of the aggregates to plug into the rental forecasts, so we have to forecast the latter as well. However, the use of forecasts for the independent variables from other sources will not necessarily resolve this problem. Long-run effects could be another reason for this finding.

Table 6. Percentage of Correct Sign Predictions for the Changes in Rents Series

	Steps Ahead							
Models	1	2	3	4	5	6	7	8
	Panel A: LaSalle Investment Management Rents Series							
VAR(1)	62	45	40	40	34	33	31	29
VAR(2)	80	75	72	67	61	63	56	47
AR(2)	80	80	79	81	73	75	74	71
Long term mean	40	39	40	38	34	33	31	32
	Panel B: CB Hillier Parker Rents Series							
VAR(1)	76	66	67	69	49	43	41	47
AR(2)	78	80	81	79	73	78	77	74
Long term mean	42	41	42	40	34	35	33	34

Note: The random walk in levels model cannot, by definition, produce sign predictions, since the predicted change is always zero.

Finally, Table 6 provides the results in terms of the percentage of correct sign predictions for the changes in rents. The percentage of correct direction predictions for the AR(2) model is impressive in particular for a horizon of up to four quarters ahead for both rent series. The accuracy of the VAR(2) model in predicting the direction of LIM rents is also good up to three quarters and then it begins to worsen. In the case of CBHP rents, the accuracy of the VAR is very good only for one quarter ahead, while the AR(2) still offers the best sign predictions, which are accurate even two years ahead. The direction predictions of the long-term mean are rather poor for both series.

4.3 *Ex ante* forecasts

Ex ante forecasts for the period immediately beyond that available at the time of writing, based on the three methodologies (excluding the random walk) are given in Table 7. Forecasts of rents in first differences are made and then forecasts of the level of real rents are computed for the period 1999 quarter two to 2001 quarter one. For the LIM index the VAR forecasts are based only on the VAR(2) specification as this has overwhelmingly outperformed the VAR(1) model.

Table 7. *Ex ante* forecasts of real retail rents

	VAR		AR		Long-term mean		VAR with exogenous forecasts	
	Changes	Real LIM index	Changes	Real LIM index	changes	Real LIM index	Changes	Real LIM index
1999:1	-	(466.2)	-	(466.2)	-	(466.2)	-	(466.2)
1999:2	5.72	472	2.88	469	1.70	468	1.80	468
1999:3	3.22	475	2.95	472	1.70	470	1.64	470
1999:4	3.68	479	2.50	475	1.70	471	1.42	471
2000:1	2.93	482	2.45	477	1.70	473	1.32	472
2000:2	2.86	485	2.21	479	1.70	475	1.76	474
2000:3	2.53	487	2.13	481	1.70	476	1.25	475
2000:4	2.42	490	1.99	483	1.70	478	1.53	477
2001:1	2.24	492	1.94	485	1.70	480	1.56	478
1999:2 to 2001:1		5.5%		4.9%		3.0%		2.7%
	VAR		AR		Long-term mean		VAR with exogenous forecasts	
	Changes	Real CBHP index	Changes	Real CBHP index	changes	Real CBHP index	Changes	Real CBHP index
1999:1	-	(592.6)	-	(592.6)	-	(592.6)	-	(592.6)
1999:2	11.37	604	7.96	601	3.15	596	8.82	601
1999:3	9.47	613	8.43	609	3.15	599	7.33	609
1999:4	8.43	622	7.61	617	3.15	602	6.71	615
2000:1	7.49	629	7.30	624	3.15	605	6.96	622
2000:2	6.73	636	6.88	631	3.15	608	6.07	628
2000:3	6.13	642	6.55	637	3.15	612	6.72	635
2000:4	5.63	648	6.24	644	3.15	615	6.66	642
2001:1	5.23	653	5.97	650	3.15	618	6.39	648
1999:2 to 2001:1		10.2%		9.7%		4.3%		9.4%

All methodologies indicate a positive increase in real retail rents over the forecast period. This increase ranges from 2.7 per cent to 5.5 per cent for LIM real rents and 4.3 to 10.2 per cent for CBHP rents. In both cases, low growth is predicted by the long-term mean model and the most optimistic forecast is obtained from the VAR model. This result is intuitive, for the VAR and AR models will attach more weight on recent observations in producing forecasts, which have shown larger increases than those seen in the early 1990's. The growth rates in real rents, forecast by the VAR and AR models, are broadly similar in each of the rent series. Finally, it can be seen that all models predict higher increases for the CBHP index.

It is possible that the forecasting accuracies of the VAR models may be blunted by not incorporating any exogenous forecasts, but rather forecasts of all variables are those estimated by the VARs themselves. In order to circumvent this problem, we use the coefficient estimates of the VAR as previously, but we replace the VAR forecasts of the future changes in GDP, and HEX with those obtained from Business Strategies Limited (BSL). Unfortunately, *ex ante* forecasts for retail sales are not, to the best of the authors' knowledge, available from any source.

The *ex ante* forecasting results from the VAR with exogenous inputs are given in the last column of Table 7. As can be seen, these forecasts are somewhat lower than those originating from the purely endogenous VAR, and this may be explained by the fact that exogenous sources appear to be anticipating a slowdown in the growth of GDP and consumer expenditure in most of the period of mid-1999 to mid-2001, whereas the pure VAR would forecast them to continue with their recent behaviour. The larger fall in the forecast rental growth for the LIM index compared with the fall in the CBHP index could be the fact that the LIM VAR model is influenced less by past values of rents and therefore it is more sensitive to economic factors[1].

The differences in the forecast growth rates between the two rent series mirrors past trends. The magnitude of increases in the CBHP rent index adjusted for inflation have historically been greater than those of the LIM index. The annual percentage growth in the CBHP index was 3.06% and for

[1] In fact, lagged rents of LIM rents (lagged two quarters) explain about 37% of contemporaneous changes in rents whereas the first lag of CBHP rents explains 63%.

the LIM index 1.76% over the sample period 1978 quarter one to 1999 quarter one. Also, it appears that in periods of rent growth, as in the late 1980s the differences in the growth rates have been wide (for example in 1989 quarter one the overall two year growth in real terms was 53.4% for the CBHP index and 36.3% for the LIM index). In the period 1990 quarter four to 1997 quarter one, a period in which real rents showed a consistent fall in real terms, the size of the two year fall in rents is very similar. The models may also pick up the fact that CBHP rental growth has persistently accelerated since 1997 quarter two whereas the LIM rent growth pattern is less clear[2].

4. Conclusions

This study undertakes a forecasting investigation of retail rents at the aggregate level with British data. It evaluates the forecasting performance of four alternative methodologies that are available to analysts for forecasting work. Three of these approaches, an autoregressive model, a long-term mean model and a random walk model, generate predictions which are based solely on the past behaviour of rents. The fourth approach, a VAR model, includes aggregates which capture conditions in the business of retailing, that is series that influence the demand for retail space, and a measure of new retail construction. These variables are those which have received most support in the existing empirical literature. The paper also provides evidence on the forecast performance of these approaches when two different rent data series, the LaSalle Investment Management and CB Hillier Parker series, are used.

Granger causality tests suggested that the VAR specification for LIM rents should be different from the VAR specification for CBHP rents. This was attributed to the dissimilar construction of the two series, their different historical behaviour and the lack of long-term influences from the

[2] The larger fall in the LIM index following the use of exogenously forecasted variables may also reflect the fact that outside forecasts are employed for two variables in the LIM VAR model compared with only one in the CBHP VAR.

analysis. The implication of this finding is that researchers need to examine whether the structure of other time-series and econometric models of retail rents are dependent on the particular series used. Forecasts are produced recursively for an up to eight-quarter ahead time horizon each time over the period 1988 quarter one to 1997 quarter one. Evaluation of the forecasts based on three criteria showed that the AR methodology is the best performing forecast approach. This is an interesting finding because it was expected that the additional information that the VAR contains, since it includes macroeconomic aggregates and construction series, would be sufficient to produce the most accurate forecasts. The fact that the additional information is forecast within the VARs could affect their performance. Another finding was the general over-prediction in all time horizons. This could imply that the average increase in rents over each of the forecast periods was lower than previously. To a degree this over-prediction may reflect the downward trend that both series of real rents exhibited over the period 1990 quarter two to 1995 quarter two. Despite the tendency of both AR and the VAR models to over-predict, the ability of the AR model, and to some extent of the VAR systems, to predict correctly the direction in the changes of retail rents was impressive.

Ex ante forecasts using all approaches indicate that real retail rents will show a positive growth in the period 1999 quarter two to 2001 quarter one. This annual growth is predicted to be higher if the CBHP index (adjusted for inflation) is used and well above the long-term mean growth of 3.06% per annum. Similarly, the annual growth in the LIM real rent index is predicted to be above the long-term mean growth (in real terms) of 1.76% per annum.

Accurate forecasts of retail rents at the aggregate level are very useful for investors. They can provide the benchmark against which the performance of local markets is assessed, since they establish broad market trends, or they can be included in cash-flow forecasts of the retail sector.

This paper has assessed commonly used simple approaches and a more complicated methodology that are at the disposal of the analyst for this purpose. The present findings have provided evidence on the forecasting ability of these approaches but the ability of other methodologies, such as simultaneous structural models, and additional variables to improve upon existing retail rent forecasts, should be the subject of ongoing research. Analysts should always, however, examine the *ex post* forecasting performance of the alternative methodologies in relation to more naïve procedures or existing models. More importantly, property market participants should be aware, when they use retail rent forecasts, that the range of the growth in rents is much dependent on the methodology and measurement series used as the findings of this study have illustrated.

References

Benjamin J, Boyle G, Sirmans C, 1990, “Retail leasing: the determinants of shopping center rents” *AREUEA Journal* **18** 302-312.

Benjamin J, Jud D, Winkler D, 1998, “A simultaneous model and empirical test of the demand and supply of retail space” *Journal of Real Estate Research* **16** 1-14.

Brooks C, Tsolacos S, 1999, “The impact of economic and financial factors on UK property performance” *Journal of Property Research* **16** 139-152.

Dickey D, Fuller W, 1979, “Distribution of the estimators for autoregressive time-series with a unit root” *Journal of the American Statistical Association* **74** 427-431.

Dickey D, Fuller W, 1981, “Likelihood ratio statistics for autoregressive time series with a unit root” *Econometrica* **49** 1057-1072.

Eppli M, Shilling J, 1996, “Changing economic perspectives on the theory of retail location” in J. Benjamin, editor, *Megatrends in Retail Real Estate*, Kluwer Academic Publishers, Boston, 65-80.

Eppli M, Shilling J, Vandell K, 1998, “What moves retail property returns at the metropolitan level? ” *Journal of Real Estate Finance and Economics* **16** 317-342.

Fraser W, 1993, *Principles of Property Pricing and Investment*, Basingstoke & London: Macmillan.

Granger C.W.J., 1969, “Investigating causal relations by econometric models and cross-spectral methods” *Econometrica* **37** 424-438.

Greene, W., 1993, *Econometric Analysis*, 2nd ed., MacMillan. New York.

Hetherington J, 1988, “Forecasting of Rents” in *Property Investment Theory* Eds. A.R. MacLeary and N. Nanthakumaran, Spon.

Hillier Parker, 1984, 1985, 1987 *A forecast of shop rents*, Hillier Parker: London. December-January.

Lachman L, Brett D, 1996, “Changing demographics and their implications for retailing” in J. Benjamin, editor, *Megatrends in Retail Real Estate*, Kluwer Academic Publishers, Boston, 43-64.

Litterman R, 1986, “Forecasting with Bayesian vector autoregressions – five years of experience” *Journal of Business and Economic Statistics* **4** 25-38.

McCue T, Kling J, 1994, “Real estate returns and the macroeconomy: some empirical evidence from real estate investment trust data 1972-1991” *Journal of Real Estate Research* **9** 5-32.

Kling J, McCue T, 1987, “Office building investment and the macroeconomy: empirical evidence, 1973-1985” *AREUEA Journal* **15** 234-55.

McGough T, Tsolacos S, 1999 “Interaction within the office market cycle in Great Britain” *Journal of Real Estate Research* **18** 219-31.

McGough T, Tsolacos S, 1995, “Predicting commercial rental values in the UK using ARIMA models” *Journal of Property Valuation and Investment* **13** 6-22.

McGough T, Tsolacos S, 1994, “Forecasting office rental values using vector-autoregressive models” *RICS Cutting Edge Conference Proceedings*, Royal Institution of Chartered Surveyors, London, 303-20.

Ownbey K, Davis K, Sundel H, 1994, “The effect of location variables on the gross rents of neighborhood shopping centers” *Journal of Real Estate Research* **9** 111-123.

RICS, 1994, *Understanding the Property Cycle* The Royal Institution of Chartered Surveyors. London.

Runkle, D.E., 1987, “Vector autoregressions and reality” *Journal of Business and Economic Statistics* **5** 437-442.

Sims C, 1980, “Macroeconomics and reality” *Econometrica* **48** 1-48.

Sirmans C, Guidry K, 1993, “The determinants of shopping center rents” *The Journal of Real Estate Research* **8** 107-115.

Tsolacos S, 1995, “An econometric model of retail rents in the United Kingdom” *Journal of Real Estate Research* **10** 519-530.