Forecasting UK Commercial Real Estate Cycle Phases With Leading Indicators: A Probit Approach

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Forthcoming ***Applied Economics***

Final Version: August 2004

Abstract

This paper examines the significance of widely used leading indicators of the UK economy for predicting the cyclical pattern of commercial real estate performance. The analysis uses monthly capital value data for UK industrials, offices and retail from the Investment Property Databank (IPD). Prospective economic indicators are drawn from three sources namely, the series used by the US Conference Board to construct their UK leading indicator and the series deployed by two private organisations, Lombard Street Research and NTC Research, to predict UK economic activity. We first identify turning points in the capital value series adopting techniques employed in the classical business cycle literature. We then estimate probit models using the leading economic indicators as independent variables and forecast the probability of different phases of capital values, that is, periods of declining and rising capital values. The forecast performance of the models is tested and found to be satisfactory. The predictability of lasting directional changes in property performance represents a useful tool for real estate investment decision-making.

Key words: Commercial real estate, turning points, leading indicators, probit models.

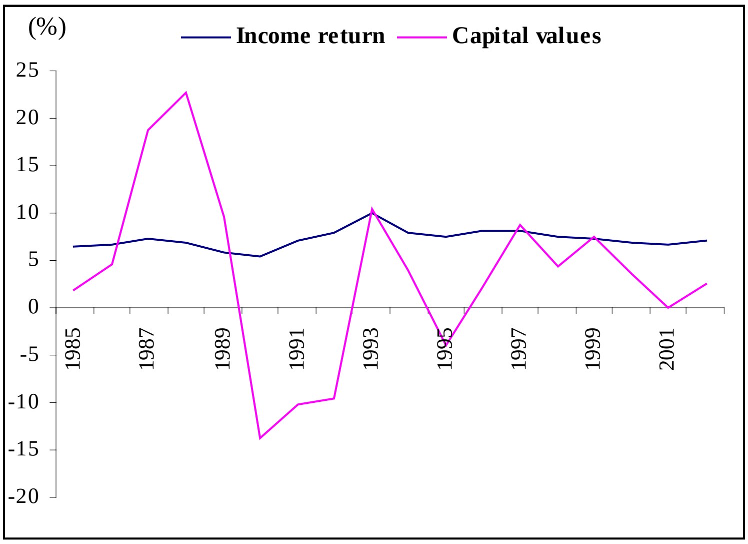
1. Introduction

The number of studies devoted to examining the performance of commercial real estate as an investment category is very small compared with studies for other asset markets, and yet real estate represents an important component of invested funds. Furthermore, there is even less published material that looks at the performance over different phases of the real state cycle. The main categories of real estate investment are in retail, office and industrial properties, although money is also allocated in other sectors such as residential and leisure. Fund managers have to make decisions on funds allocated to real estate and the mix of commercial real estate sectors in their portfolios. Institutional funds, particularly insurance, pension and unitised funds, have considerable allocations in commercial real estate, varying between 5% and 20% of total fund value.

Forecasting total returns and its components, income returns and capital values, across commercial sectors is important in making real estate allocation decisions. The consideration of the prospects for real estate as an asset class becomes more pronounced in times when real estate returns are anticipated to diverge from returns on other assets, as was the case in 2001 and 2002 when real estate delivered 6.7% and 9.7% respectively, compared with respective equities returns of -13.2% and -22.3%. Fund managers are looking to medium-term/longer-term signals in order to make *strategic* investment decisions across different asset categories and across real estate categories. Short-term signals are important for incipient turning points in total returns in order to assist fund managers in the positioning of new money and in making *tactical* decisions, which may deviate from benchmark/strategic positions.

The most volatile component of total returns in real estate performance is capital value. Over the period 1985 to 2002 capital values have fluctuated much more severely than income returns. Figure 1 illustrates the volatility of capital values in relation to income returns. It is not surprising, therefore, that investors are particularly interested in tracking and predicting the capital value component of total returns for the office, retail and industrial sectors. Capital values capture both the existing passing rents and the expectations of future rental growth. The measurement of capital values will also reflect any capital expenditure incurred.

Figure 1: **Income returns and capital value growth for all property**



<u>Source:</u> Investment Property Databank

The broad objective of this study is to predict capital value movements in the industrial, office and retail sectors. Specifically, this study examines the potential of commonly used leading indicators for predicting phases of decline and expansion in industrial, office and retail capital values. A key objective is to provide empirical evidence that would be useful for investors to gauge capital value movements in the short-run. The analysis is also motivated by the fact that little attention in the existing real estate literature has been directed towards predicting capital values, the bulk of the research being concentrated on modelling and forecasting rental growth.

The leading indicator approach is directed towards anticipating business fluctuations and is rooted in the view that there are repetitive sequences of expansion and contraction in economic activity. Leading economic indicators are series that peak before the macro-economy peaks and reach a trough before the macro-economy moves into an expansionary phase. The basic rationale is to identify these occurrences, date them and forecast the emerging stages. In practice, this means identifying the early stages of a recession or a recovery. A considerable amount of research on business cycles has focused on the usefulness of leading indicators in predicting turning points in economic activity. Many organisations, such as the OECD, the European Commission, the US Conference Board**,** as well as private firms, monitor selected series and have constructed composite leading indicators to predict turning points in the business cycle. Given the close relationship between the economy and the commercial real estate market, if leading indicator series can successfully anticipate trends in the economy, these may well provide *early* signals for future commercial real estate performance.

There is a wide literature examining the relationship between leading indicators and the variables selected to account for the business cycle. The techniques employed range from standard causality and switching regime models to binary models. In this study we estimate a probit regression model, using the leading economic series as independent variables, to forecast the probability of different phases in real estate capital values i.e. periods of sustained rise or decline in capital values. The list of potential leading indicators can be large. We use as prospective indicators the constituent series of the composite leading indicators of the UK economy produced by the US Conference Board and two private organisations, Lombard Street Research and NTC Research.

The remainder of this paper is organised into the following sections. Section two outlines the methodology for dating the turning points and phases (of contraction and expansion) in the UK commercial real estate capital values series. Section three describes the indicators and the data. We subsequently outline the probit model, the methodology used for forecasting sustained periods of decline in the capital values series with leading economic indicator series. Section four presents the results: in-sample probit models with both individual indicator variables and with vectors of indicator variables, together with out-of-sample (recursive) forecasts. The predictive performance of the probit models is evaluated. The implications of the approach for identifying signals in economic indicators for subsequent real estate performance are discussed in section five. Section six provides concluding remarks.

2. Methodology

2.1 Dating turning points

The first stage of the analysis identifies and dates the turning points in commercial real estate capital values. A number of mechanical rules can be deployed for distinguishing between the different phases of the cycle.

In business cycle measurement, two very different but complementary approaches exist. According to the “growth cycles” approach, periods of expansion and contraction are represented as cyclical movements around a trend, which first needs to be estimated. When researchers calibrate real business cycle models, the business cycle is typically found by de-trending the data by applying, for example, a Hodrick-Prescott filter or similar method. In contrast, in the “classical cycles” approach, periods of expansion and contraction are represented by the level of activity; one attempts to identify significant turning points – peaks and troughs – and define a contraction to simply be the time from peak to trough, and an expansion to be the time from trough to peak.

Our methodology for dating the different phases in the capital values series is based on the classical business cycle approach for a number of reasons. Most importantly, it seems self-evident that identifying periods of lasting absolute declines in capital values is more important for real estate forecasting and property investment analysis than declines relative to a trend. But there are also technical advantages in choosing this approach where no trend modelling is needed. It has been shown that different de-trending methods may yield different growth cycle chronologies (Canova, 1998) and that commonly used de-trending methods may induce spurious cycles (King and Rebelo, 1993, and Osborn, 1995). In business cycle research, there are on-going extensive discussions of what are appropriate "trend removal" filters – see Hodrick and Prescott (1997), Christiano and Fitzgerald (1998), Baxter and King (1999) and Corbae *et al* (2001).

The standard point of reference for dating classical business cycles is the analytical recursion of Bry and Boschan (1971). Versions of this have been used by Mintz (1969), King and Plosser (1994), Watson (1994) and Artis, Kontolemis and Osborn (1997), among many others. The general idea is to perform different degrees of smoothing on the data in order to locate neighbourhoods of potential turning points, which are then finalised using the raw data. The main characteristic of these methods is that the values of the series before and after the turning point follow a distinctly different direction. The cycles implied by the turning points are required to satisfy a minimum defined duration.

Although these methodologies remain subjective they provide insights into identifying turning points. In this study we apply a version of the Bry and Boschan (*op.cit*) procedure. We define a turning-point date as occurring when a swing in one direction ends and a swing in another direction begins. Table 1 provides a summary of the rules we use to identify turning points in the log-levels of the monthly IPD capital value series over the sample 1986:12-2002:04.

Table 1: **Procedure for Dating Peaks and Troughs in Real Estate Capital Values**

- Three- month moving average in log capital values index
- Three month window
- Peak: $t-3 < t > t+3$
- Trough: $t-3 > t < t+3$
- Once a peak or a trough is indicated, the next phase (i.e. positive or negative growth in capital values should last at least for six months)

The original capital values are smoothed by using a centred moving average of three months to reduce the impact of short-term erratic fluctuations. A peak (trough) is identified at *t* in this smoothed series if the value of the variable is strictly higher (lower) than the values for three months on either side, with peaks and troughs required to alternate and phases to have a minimum duration of six months. Turning points are determined on smoothed and unsmoothed series and points on the unsmoothed series that are not approximately matched by points on the smoothed series are excluded. We experiment with different degrees of smoothing on the data and different windows. The procedure described in Table 2 best fits the data. Table 2 shows the turning points for the three broad real estate categories identified by this procedure (a plot of the logs of the capital value series is shown in Appendix A).

Table 2: **Classical turning points in the IPD UK Capital Value Series**

Industrial Properties		**Office Properties**		**Retail Properties**	
Date	Peak or Trough	Date	Peak or Trough	Date	Peak or Trough
1989:10	Peak	1989:11	Peak	1989:08	Peak
1993:04	Trough	1993:04	Trough	1993:02	Trough
1994:06	Peak	1994:04	Peak	1994:09	Peak
1996:05	Trough	1996:09	Trough	1996:03	Trough
2001:03	Peak	2001:05	Peak	2000:04	Peak
				2001:09	Trough

Having dated the peaks and troughs, each time period can be identified as either one of expansion or one of contraction. Periods of expansion start with the observation following a trough and run to (and include) the date/month of the subsequent peak. Periods of contraction start with the observation following a peak and run to the next trough.

2.2 The probit approach

The probit approach is the one of the most frequently used methodologies to assess the usefulness of leading indicators in predicting turning points (Boulier and Steckler, 2001, Chin, Geweke and Miller, 2000, and Estrella and Mishkin, 1998). The problem is defined as one where we account for the behaviour of a dichotomous dependent variable that describes two alternatives, the incidence of either being or not being in a phase of contraction. A probit model is deployed to compute probabilities that a contraction (T) in capital values will occur at given values of a set of leading indicator variables (x).

We define a variable T so that:

$T = 1$ for the period that capital values decline

$T = 0$ otherwise

Therefore, the objective of using a probit approach is to estimate a response probability:

$$\Pr(T = 1 \mid \boldsymbol{x}) = \Pr(T = 1 \mid x_1, x_2, \ldots x_k) \tag{1}$$

where $\boldsymbol{x}$ denotes the full set of explanatory variables (x_1, x_2, … x_k) – a vector of leading indicator series in the present study – that *a priori* affect the direction of capital value movements. Based on equation (1) the probit model can be written as:

$$\Pr(T = 1 \mid \boldsymbol{x}) = F(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k) = F(\beta_0 + \boldsymbol{x\beta}) \qquad (2)$$

where F is a function taking on values strictly between zero and one, which ensures that the estimated response probabilities are strictly between zero and one; $\boldsymbol{\beta}$ is the set of coefficients corresponding to the indicator variables $\boldsymbol{x}$.

In order to make the probit approach operational we link the probability of obtaining $T = 1$ to an unobservable index I. This index may represent a signal index or economic conditions index upon which judgements of a forthcoming turning point are made. The higher the value of the index I the greater the probability that $T = 1$.

The unobservable index I, which is required to be normally distributed for a probit to apply, is determined by the set of explanatory variables $\boldsymbol{x}$:

$$I = \beta_0 + \boldsymbol{x\beta} \qquad (3)$$

A threshold value is also required to indicate the possible occurrence of a contraction phase in capital values. If the estimated I is greater than a threshold value I^*, then $T = 1$:

$$\Pr(T = 1 \mid \boldsymbol{x}) = \Pr(I^* \leq I) = \Pr(I^* \leq \beta_0 + \boldsymbol{x\beta}) \qquad (4)$$

The probit model will estimate the coefficients β_0 and $\boldsymbol{\beta}$ and also the unobservable series I. Once an estimate for I is obtained we can accept $T = 1$ (contraction) if I is greater than I^*, the threshold value of I. The normality assumption for the unobservable index I means that we can obtain the probability that $I^* \leq I$ from the standardised normal cumulative density function. Therefore:

$$\Pr(I^* \leq I) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{I} e^{-t^2/2} dt = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\beta_0 + \beta x} e^{-t^2/2} dt \qquad (5)$$

where, t ~ $N(0, 1)$.

The probability of a contraction ($\Pr(T = 1)$) is therefore measured by the area of the standard normal cumulative curve from -∞ to I. A contraction, therefore, will be more likely to occur the larger the value of I. Equation (5) shows the probability that a standard normal variable (I in this case) will be less than or equal to the threshold I^*.

3. Data

The industrial, office and retail capital value series are obtained from Investment Property Databank's monthly database. The capital values series covers the period 1986:12-2002:04.

The set of variables used contains the constituent series of the leading indicators for the UK produced by the Conference Board, Lombard Street Research and NTC Research. Table 3 shows the leading indicator series that enter the probit regressions. The source of the data is Thomson Financial Datastream and the Office for National Statistics.

Table 3: Leading indicators

Gilt yields	Car registrations	Net lending to consumers
Export orders	Volume of expected output	Financial Surplus\Deficit
Consumer confidence	Stock of finished goods	Real money supply M4
Changes in inventories	Consumer credit	Personal disposable income
Industrial production	Unit labour costs	Gross trading profits
House building starts	Yield curve	Manufacturing investment
Real money supply M0	Press recruitment ads.	Private to total credit
New orders in manufacturing	FT All Share price Index	
Manufacturing employment	Retail sales	

As a preliminary to the analysis, the stationarity characteristics of each indicator series were examined using the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981)[1]. A linear trend is added if the plot of the log of the series is dominated by a trend. The ADF results suggest that most of the series are I(1). The time series are transformed by taking logs and into annual growth rates[2].

[1] The results of the unit root tests are available from the authors on request.
[2] We also experimented with quarterly growth rates but the annual figures yield better models.

4. Estimated Models

4.1 Univariate Probits

Given the large number of variables entering the analysis it is considered practical to run univariate probits and assess the ability of the individual leading indicators to predict turning points in capital values in the three property sectors. Table 4 presents results of the univariate probits: the lags of the individual leading indicators that performed best are based on the significance of the *z*-statistic and the modified McFadden R^2 (as developed by Estrella 1998). The modified McFadden R^2 is a simple measure of goodness of fit that corresponds intuitively to the widely used coefficient of determination, R^2, in a standard linear regression.[3] But unlike the R^2 in the standard linear regression, in the analysis employed in this study even low values of the modified McFadden R^2 (i.e. greater than 0.25) are considered acceptable (see Estrella and Mishkin *op.cit*).

The negative sign associated with the *z*-statistic indicates that the variable is inversely related to the probability of a contraction in capital values. That is, as the leading indicator takes a higher value, the probability of a subsequent decline in capital values diminishes. The only leading indicator that has a positive *z*-statistic is the gilt yield. This, in turn, suggests the higher the value of gilt yields the higher the probability that capital values will enter a declining phase.

The variable that achieves the best performance on the basis of the modified McFadden R^2 is the ratio of private to total credit. The most significant explanatory variables for the industrial capital values model are press recruitment ads and gross trading profits; for the retail model it is new car registrations and retail sales. The highest achieved explanatory power is for offices. Overall, these leading indicators appear to predict turning points more successfully for office and industrial capital values than for retail capital values.

Some patterns emerge for the most significant lags of the leading indicators. Retail sales post the longest lag in all sectors (and in all cases the modified McFadden R^2 is of the highest in each sector). With the exception of the gilt yield and consumer confidence, the leading indicators predict turning points earlier in offices than in industrial and retail (for retail many of the indicators are coincident). The exception is the gilt yield, which has a lag of 5 months in retail and a lag of two months in industrials and offices, and M4 money supply and private to total credit (lag of six months for retail capital values and of five months for

[3] The original McFadden R^2 is defined as $1\text{-}L_u/L_c$, where L_u is the unconstrained Log-Likelihood (in the probit regression) and L_c the constrained Log-Likelihood (β=0 in equation (2)). The version proposed in Estrella (*op cit.*), which we use in this paper, furthermore adjusts for the number of regressors. The measure takes on values between 0 and 1. A value that is close to 0 indicates that the variable or variables in the model have little explanatory power, a value close to 1 indicates a very close fit and intermediate values may be used to rank the models in terms of predictive power.

Table 4: In-sample univariate probit models

	Office	Industrial	Retail
M0 Money Supply	k=6	k=4	k=0
McFadden R^2*	0.24	0.24	0.23
z-statistic	-7.19	-7.08	-6.61
M4 Money Supply	k=9	k=5	k=6
McFadden R^2	0.26	0.27	0.29
z-statistic	-7.39	-7.11	-7.60
Press Recruitment Ads	k=4	k=2	k=0
McFadden R^2	0.33	0.43	0.23
z-statistic	-8.34	-9.21	-5.24
Gross Trading Profits	k=5	k=4	k=0
McFadden R^2	0.37	0.42	0.31
z-statistic	-7.24	-7.40	-5.96
Housebuilding Starts	k=5	k=5	k=1
McFadden R^2	0.18	0.20	0.29
z-statistic	-5.91	-6.27	-6.64
New Car Registrations	k=5	k=8	k=6
McFadden R^2	0.17	0.18	0.35
z-statistic	-4.75	-4.68	-5.93
Retail Sales	k=12	k=12	k=10
McFadden R^2	0.41	0.38	0.35
z-statistic	-6.55	-6.07	-5.14
Industrial Production	k=6	k=4	k=0
McFadden R^2	0.33	0.37	0.18
z-statistic	-5.06	-5.05	-4.96
Consumer Confidence	k=4	k=5	k=0
McFadden R^2	0.40	0.37	0.29
z-statistic	-8.01	-7.61	-7.60
Gilt Yields (10yrs)	k=2	k=2	k=5
McFadden R^2	0.20	0.20	0.24
z-statistic	7.36	7.28	7.42
Private to Total Credit	k=8	k=5	k=6
McFadden R^2	0.50	0.38	0.18
z-statistic	-7.68	-6.38	-5.49

k: number of lags. The lag order is determined by the maximisation of the modified McFadden R^2.
*denotes the modified McFadden R^2.

industrial capital values). The in-sample probit results presented in Table 4 are both illustrative and useful in model selection.

4.2 Multivariate probits

We proceed by next examining how well different vectors/combinations of the explanatory variables (presented in Table 4) can predict contractions. The choice of variables follows the general to specific approach. Four criteria are used for the selection of the variables: (i) the value of the modified McFadden R^2 increases significantly with the addition of an extra variable and the addition of the extra variable reduces the value of the Akaike Information Criterion (AIC); (ii) the variables take the expected sign; (iii) the coefficients on the variables are statistically significant at the 10% level of significance; (iv) the coefficients carry the same sign and are significant in sub-samples. The equations reported in Tables 5-7 are the ones that perform best with respect to the above criteria.[4]

Table 5: **Probit estimates for industrial capital values**

Dependent variable: Industrial capital values			
Variable	Coef.	*z*-stat.	Prob.
Constant	3.4	6.3	0.00
M4(-5)	-27.9	-6.9	0.00
GILTY(-2)	11.0	6.6	0.00
IP(-4)	-0.4	-4.3	0.00
McFadden R^2	0.66		
Mod. McFadden R^2	0.77		
Probability (LR stat.)	0.00		
Sample period: 1986:12 to 2002:04 (185 observations)			
Standard errors estimated with the Huber-White method			

Table 6: **Probit estimates for office capital values**

Dependent variable: Office capital values			
Variable	Coef.	*z*-stat.	Prob.
Constant	3.0	7.3	0.00
M4(-9)	-27.4	-6.4	0.00
GILTY(-2)	12.0	6.5	0.00
IP(-6)	-0.3	-5.2	0.00
McFadden R^2	0.66		
Mod. McFadden R^2	0.78		
Probability (LR stat.)	0.00		
Sample period: 1987:01 to 2002:04 (184)			
Standard errors estimated with the Huber-White method			

[4] This is not to say that other vectors of leading indicators are not significant. For example, when the equations in Tables 5 and 6 are estimated with gross trading profits or press recruitment adds instead of industrial production, they are well specified and robust. However, when industrial production is included in the vector of explanatory variables, the significance of the former variables diminishes and they are excluded from the analysis, as it appears they contain information already incorporated in industrial production.

Table 7: **Probit estimates for retail capital values**

Dependent variable: Retail capital values			
Variable	Coef.	*z*-stat.	Prob.
Constant	2.0	6.0	0.00
M4(-6)	-27.3	-7.0	0.00
GILTY(-5)	11.4	5.4	0.00
CARREG(-6)	-7.8	-4.3	0.00
McFadden R^2	0.61		
Mod. McFadden R^2	0.72		
Probability (LR stat.)	0.00		
Sample period: 1986:12 to 2002:04 (185)			
Standard errors estimated with the Huber-White method			

The explanatory variables in the equations reported above have the expected signs. Thus, as broad money supply, industrial production and new car registrations increase, the probability of a subsequent sustained decline in capital values diminishes. And, as the gilt yields increase, the probability of a subsequent decline becomes greater.

From the equations reported above we can conclude that the findings are consistent across sectors. The office model performs slightly better in terms of the modified McFadden R^2. Two indicators, the M4 measure of money supply and the gilt yield enter the vector of explanatory variables in all sectors. For office and industrial capital values industrial production is also significant, while for retail the car registrations series is significant.

5. How well do the models predict?

In evaluating the forecasts of the probit models, we first calculate the out-of-sample forecasts in the following way: First, the model is estimated using data from the beginning of the sample up to a given month. The estimated model is then used to form projections *k* months ahead, where *k* is the minimum number of lags of the independent variables in the model[5]. After adding one more month to the estimation period, this procedure is repeated and rolling regressions are run for each subsequent month. Data that become available subsequent to the prediction date are used neither to estimate nor to predict. In this way, the procedure yields what a statistical model would have predicted with the information only available at any point in the past. It is a more realistic test of the predictive ability of the various models than the in-sample results. The recursive probabilities calculated this way for all three sectors cover the period from 1994:01 to 2002:04.

[5] In the office and industrial equations *k*=2, thus we have out-of-sample forecasts two months ahead, in the retail equation *k*=5, and we have forecasts 5 months ahead.

In Figures 2, 3 and 4 the grey shaded areas represent the actual periods of declining capital values. The solid line indicates the in-sample probabilities, based on coefficients estimated using the entire sample from December 1986 through April 2002. The dashed line indicates the out-of-sample probabilities: the probabilities are based on the information actually available at each point in time. Rising lines indicate increasing probabilities that signal a forthcoming contraction in capital values and vice versa.

Figure 2: Industrial, In-Sample versus Out-of-Sample Probabilities 2 Months Ahead

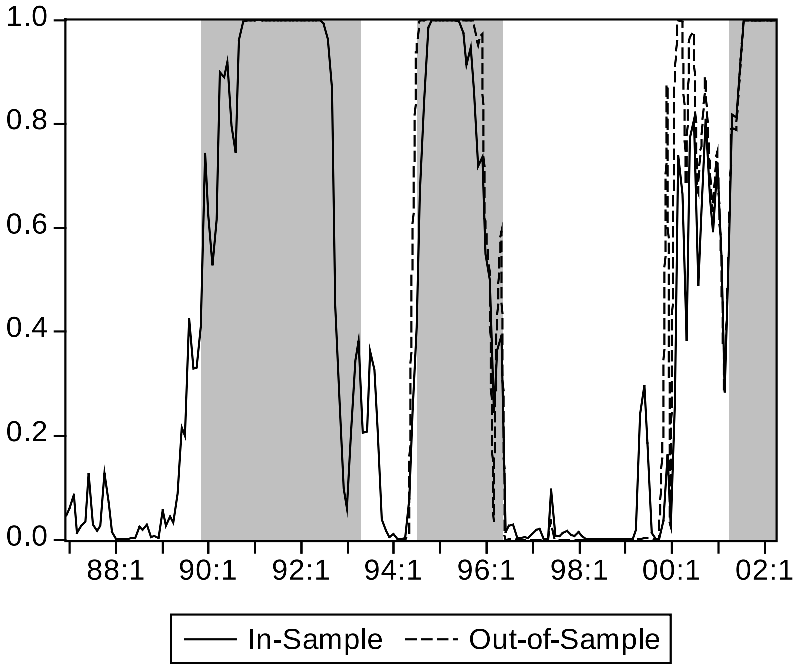


Figure 3: Offices, In-Sample versus Out-of-Sample Probabilities 2 Months Ahead

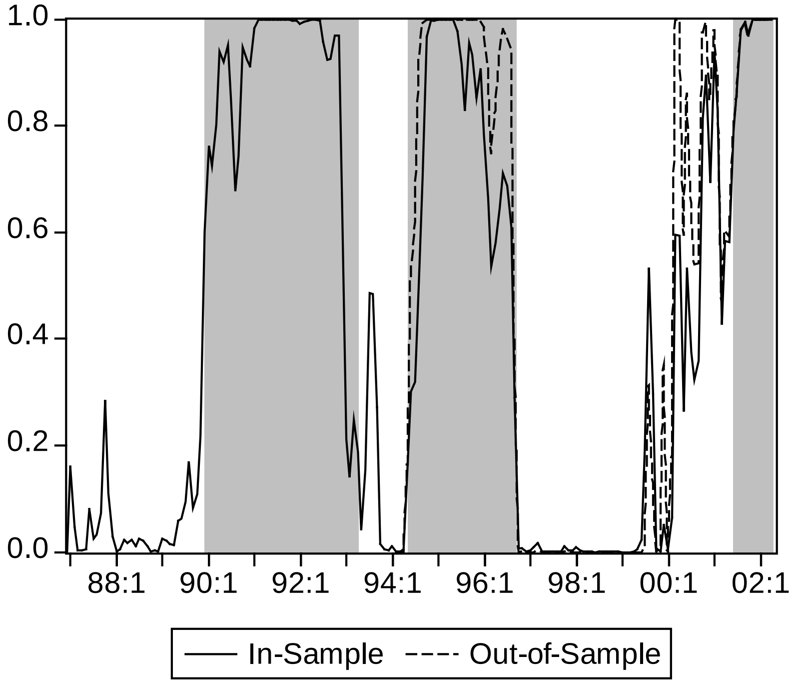
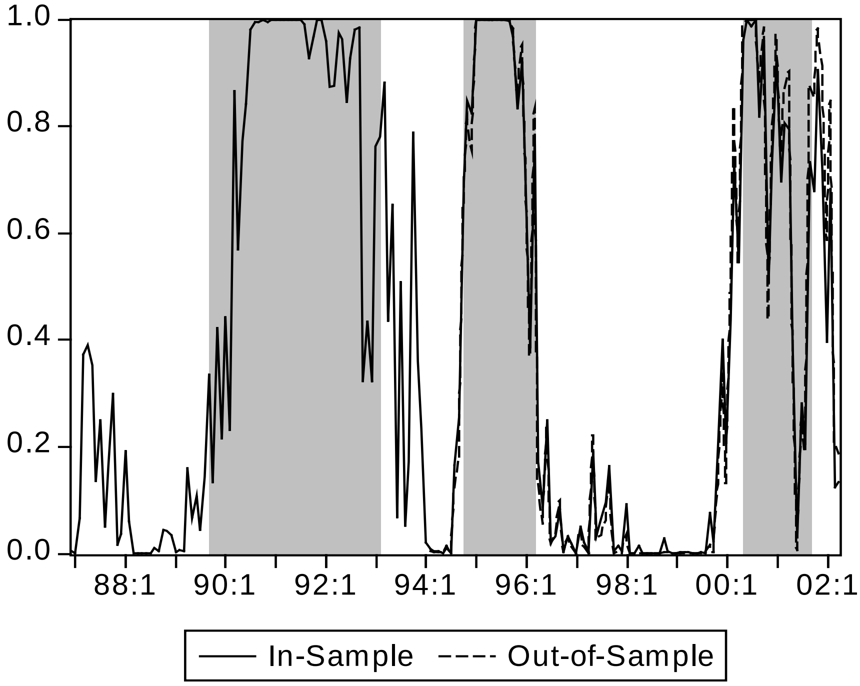


Figure 3: Retail, In-Sample versus Out-of-Sample Probabilities 5 Months Ahead



The in-sample probabilities do not differ substantially from the out-of-sample ones and the prediction record seems about the same throughout the sample. We would expect the solid line, representing the in-sample – with full information – forecasts, to perform better than the out-of-sample forecasts. On a number of occasions (i.e. industrial capital values in the period 1994 to 1996 and retail capital values in the period 2001-2002) the performance of the probit is very good. On other occasions (i.e. office and industrial capital values in 2001) the probit had indicated a fall in capital values that did not actually occur.

Although rising (falling) probabilities in Figures 2, 3 and 4 signal a turning point in capital values, for the formal determination of whether these probabilities constitute a prediction of a phase of declining (increasing) capital values, a threshold level of these probability estimates must be selected. If the forecast probability exceeds this threshold value, a phase of sustained decline in capital values is predicted. It is then possible to determine the number of contractions that were predicted, the number that were not predicted (Type I error) and the number of times a prediction was made and there was no decline in capital values (Type II error).

In Table 8 we show the out-of-sample-performance evaluation of the *industrial* probit model for different thresholds[6] and compare its out-of-sample forecasting record against a naïve benchmark, the "constant probability" model. The "constant probability" model is a model that includes only the intercept term *c*.

Table 8: **Prediction evaluation for the recursive industrial probit: 1994:01-2002:04**

70% Threshold probability

Prediction of a decline in capital values	**Probit model** Actual decline in capital values			**Constant probability model** Actual decline in capital values		
	No	*Yes*	Total	*No*	*Yes*	Total
No	53	6	59	63	36	99
Yes	10	30	40	0	0	0
Total	63	36	99	63	36	99
% Correct	84.1	83.3	83.8	100	0	63.6

90% Threshold probability

Prediction of a decline in capital values	**Probit model** Actual decline in capital values			**Constant probability model** Actual decline in capital values		
	No	*Yes*	Total	*No*	*Yes*	Total
No	59	8	67	63	36	99
Yes	4	28	32	0	0	0
Total	63	36	99	63	36	99
% Correct	93.6	77.8	87.9	100	0	63.6

[6] The selection of the cut-off point is arbitrary. In the business cycle literature it ranges from 0.25, when an individual variable is used to predict recessions, to over 0.9, when indices of leading series are employed.

When a threshold probability of 0.7 is used, 53 of the 63 of the *No decline (T=0)* observations and 30 of the 36 of the *Yes* (*T*=1) observations are correctly classified by the estimated model. Overall, the estimated model correctly predicts 83.8% of the observations (84.1% of the *T*=0 and 83.3% of the *T*=1 observations). It is 20.2% better at predicting responses than the constant probability model. When a threshold of 0.9 is used, the estimated model correctly predicts 87.9% of the observations. It is 24.3% better at predicting than the constant probability model.

The out-of-sample prediction evaluation for the office and retail probit models (shown in Appendix B) reveals similar performance. When a threshold of 0.7 is employed, both the office and retail probit models correctly predict 87.9% of the observations. The office probit is 28.3% more successful at predicting responses than the constant probability model; the retail probit is 23.2% more successful. When the threshold is set at 0.9, the office model correctly predicts 86.8% of the observations – 27.3% better than the naïve benchmark. The retail model correctly predicts 80.8% of the observations – 16.1% better than the naïve benchmark.

The out-of-sample performance of the probits is acceptable. Although the evaluation reveals a number of false predictions of declining capital values and failures to predict a contraction in capital values in some months, the predictions obtained from these recursive models are significantly superior to those of the naive (constant probability) model.[7] Thus, the probit models with leading indicators appear to provide useful information for the future direction of capital values.

6. Conclusions

There is a wide literature on modelling and predicting real estate markets. Structural and reduced equation models of real estate performance as well as models that relax the restrictions of structural models, such as unrestricted vector autoregressions, have been traditionally employed to obtain quantitative forecasts of real estate variables.

In addition to the conventional quantitative analysis, real estate analysts are increasingly monitoring several economic series in search of early signals for property market activity. This becomes more important at times of uncertainty arising from unsettling economic conditions and volatility in the wider investment markets. Leading indicators can prove useful to real estate analysts for the purpose of judging the direction in the economy and real estate market in the short-run; these series are available on a frequent basis and are considered to provide early signals of future economic activity. Since leading indicators are based on

[7] In-sample performance Tables over the whole sample period are available from the authors upon request.

business cycle stylised facts they offer additional judgemental information that is likely to affect sentiment in real estate markets. Hence, directional forecasts (as an alternative to point forecasts) based on leading indicators represent a useful analytical tool for real estate investment.

The present study employs leading indicators to predict phases in real estate cycles. Following the literature on classical business cycles, a probit model is deployed to examine whether commonly used economic, financial and survey series provide information on the future direction of capital values. The model uses as inputs series that are constituents of business cycle leading indicators and estimates probabilities of sustained increases or declines in real estate capital values. The probit approach links the information contained in leading indicators to trends in capital values. It provides real estate analysts with a gauge to rising or falling capital values without recourse to uncertain point forecasts.

Our study is helpful in determining which particular indicators of the UK economy are worth monitoring in predicting the direction in UK commercial property capital values. Two indicators, the gilt yield and broad money supply (M4), enter the vector of explanatory variables for all three real estate sectors analysed. For the office and industrial sectors, industrial production is also significant. For retail capital values the car registrations series is significant. There is, therefore, a high degree of consistency in the multivariate probit findings with respect to the subset of included indicators.

The out-of-sample forecast performance of the models is very good. The probit forecasts improve upon the predictions of the naïve model. Hence, there is evidence in the present study that probit models offer a valuable means for turning point detection in the commercial property markets. Investment decision-making benefits from information on the timing and probabilities of directional changes in the trajectories of real estate performance measures. It follows that an amalgamation of structural models and less theoretically restrictive approaches such as binary models is likely to increase the quality of real estate forecasts and, therefore, investment decisions.

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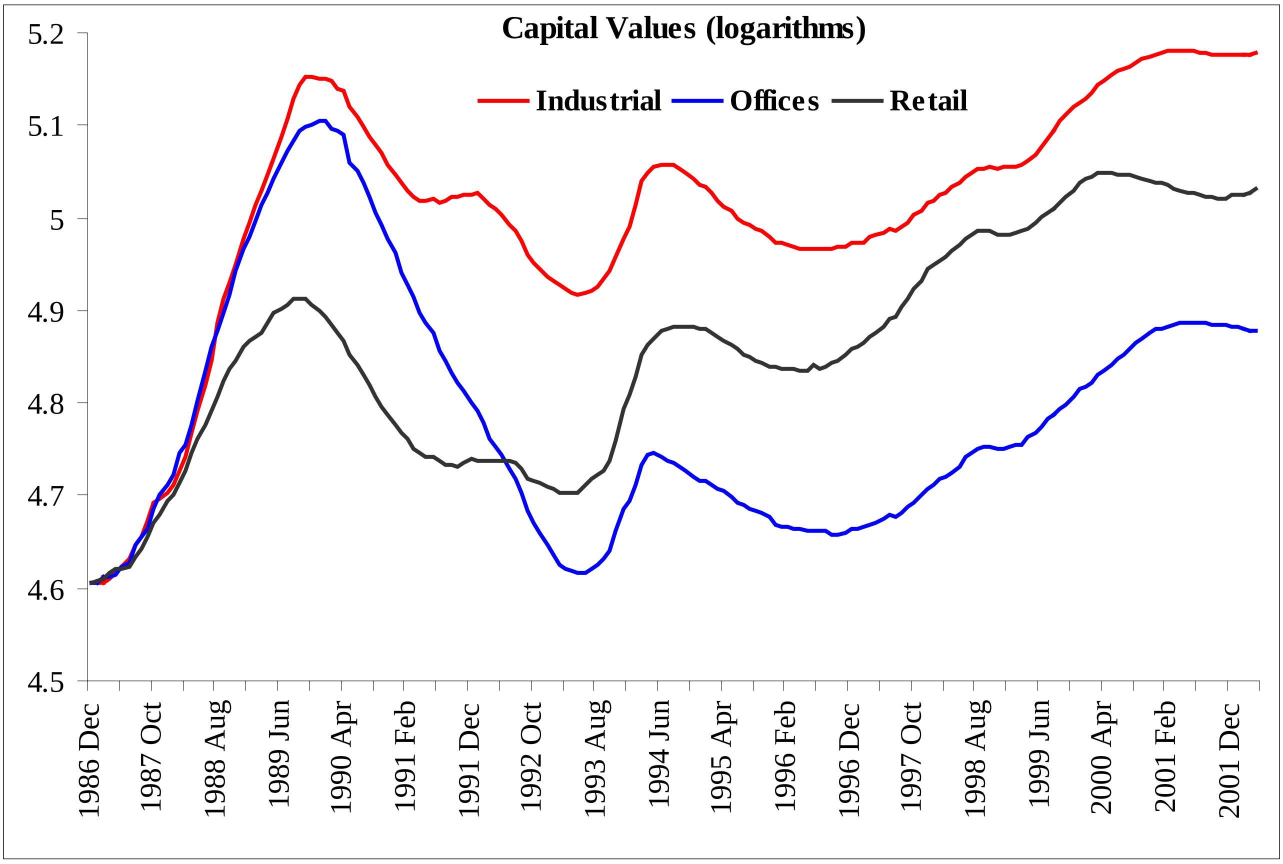
APPENDIX A



Source: IPD

APPENDIX B

Prediction evaluation for the recursive office probit: 1994:01-2002:04

70% Threshold probability

	Probit model			**Constant probability model**		
Prediction of a decline in capital values	**Actual decline in capital values**			**Actual decline in capital values**		
	No	*Yes*	Total	*No*	*Yes*	Total
No	51	4	55	59	40	99
Yes	8	36	44	0	0	0
Total	59	40	99	59	40	99
% Correct	86.4	90	87.9	100	0	59.6

90% Threshold probability

	Probit model			**Constant probability model**		
Prediction of a decline in capital values	**Actual decline in capital values**			**Actual decline in capital values**		
	No	*Yes*	Total	*No*	*Yes*	Total
No	54	8	62	59	40	99
Yes	5	32	37	0	0	0
Total	59	40	99	59	40	99
% Correct	91.5	80	86.8	100	0	59.6

Prediction evaluation for the recursive retail probit: 1994:01-2002:04

70% Threshold probability

	Probit model			**Constant probability model**		
Prediction of a decline in capital values	**Actual decline in capital values**			**Actual decline in capital values**		
	No	*Yes*	Total	*No*	*Yes*	Total
No	59	7	66	64	35	99
Yes	5	28	33	0	0	0
Total	64	35	99	64	35	99
% Correct	92.2	80	87.9	100	0	64.7

90% Threshold probability

	Probit model			**Constant probability model**		
Prediction of a decline in capital values	**Actual decline in capital values**			**Actual decline in capital values**		
	No	*Yes*	Total	*No*	*Yes*	Total
No	62	17	79	64	35	99
Yes	2	18	20	0	0	0
Total	64	35	99	64	35	99
% Correct	96.9	51.4	80.8	100	0	64.7