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IPF Research Awards 2024
Reconciling the Predictability of Returns from Commercial Real Estate Yields

COMMISSIONED BY THE IPF RESEARCH PROGRAMME

This research was funded and commissioned through an extension to the IPF Research Programme 2022-2025.

This Programme supports the IPF's wider goals of enhancing the understanding and efficiency of property as an investment. The initiative provides the UK property investment market with the ability to deliver substantial, objective and high-quality analysis on a structured basis. It encourages the whole industry to engage with other financial markets, the wider business community and government on a range of complementary issues.

The Programme is funded by a cross-section of businesses, representing key market participants. The IPF gratefully acknowledges the support of these contributing organisations:

INTRODUCTION

In 2024, the IPF Research Programme launched its third grants scheme to provide financial assistance to promote real estate investment research. No specific themes were suggested and prospective applicants were encouraged to examine issues that would advance the real estate investment industry's understanding of and implications for asset pricing, risk-adjusted performance and investment strategy. The scheme was also open to individuals, working within institutional organisations, where the grant may be used to fund data acquisition.

The Grant scheme was first run in 2021, when three applicants were awarded grants, and again in 2023, when the programme provided grants for six successful submissions. This time, an appraisal of proposals received by the deadline of 30 September 2024 resulted in the provision of grants to two submissions, with limited supervision afforded by a sub-committee of the IPF Research Steering Group during the research period.

Each paper is available to download from the IPF website. We hope you find them a diverse and interesting read.

The following paper has been written by Nick Mansley, Zilong Wang and Colin Lizieri, University of Cambridge.

Richard Gwilliam
Chair IPF Research Steering Group
October 2025

Executive Summary

This study investigates the predictive power of commercial real estate (CRE) yields, specifically the cap rate, for future excess returns (the difference between total return and Government bond yield) in the UK. Cap rates vary over time, and these changes can be attributed to shifts in expected cash flow growth, risk-free rates, or risk premia. A high cap rate theoretically implies either a high property expected return or low expected rental growth, suggesting it should predict higher ex-post returns or lower ex-post rental growth, or a combination of both.

Previous research has shown the real estate cap rate's relationship with ex-post returns to be inconsistent and unstable. The central finding of this study is that the instability in cap rate forecasts is primarily attributable to structural breaks in the cap rate's steady-state mean (or equilibrium level). To account for this, the study introduces an adjusted cap rate, defined as the deviation of the cap rate from its current steady-state mean. Utilising this adjustment substantially improves the in-sample forecasting power, demonstrating a strong ability to forecast excess returns for UK office, retail, and industrial properties across 8- to 20-quarter horizons. This validates the adjusted cap rate as a robust in-sample predictor.

While the adjusted cap rate performs well in-sample, real-time forecasting presents two major challenges for investors: estimating if there has been a break (and its timing) and accurately determining the new mean cap rate after a break, especially when limited post-break data is available. The study's analysis indicates that accurately estimating the timing of the break is not the primary issue, as breaks can be detected quickly (typically within nine quarters). Conversely, the estimation of the magnitude of the change in the mean cap rate after the break entails substantial uncertainty. Despite these challenges, the out-of-sample forecasts using the adjusted cap rate outperform a random walk model for office and retail properties (though not industrial) and consistently outperform the unadjusted cap rate forecasts.

In conclusion, this research provides evidence that the cap rate's predictive power for CRE excess returns is restored once structural breaks are accounted for. The study's main contribution is the identification of structural breaks in the steady-state mean as the source of forecast instability and the introduction of the adjusted cap rate as a superior predictor. For market participants, the key takeaway is the necessity to test for structural breaks and to utilise the adjusted cap rate (deviation from the current steady-state mean) for more robust forecasting and investment appraisal.

Reconciling the Predictability of Returns from Commercial Real Estate Yields

Nick Mansley[a], Zilong Wang[a] and Colin Lizieri[a]

[a] *Department of Land Economy, University of Cambridge, UK*

1. Introduction

Returns from real estate can be seen as driven by the commercial real estate yield at the start and changes in the cap rate and income over the holding period. Cap rates vary over time and these changes can be attributed to changes in expected cash flow growth, risk-free rates, or risk premia. A high cap rate implies either a high property expected return, or low expected rental growth, or a combination of both. One implication is that a higher cap rate should predict higher ex-post returns and/or lower ex-post rental growth. From the stock market literature (see, among others, Campbell, 1991; Cochrane, 1992), most of the variation in dividend yields is attributed to changing forecasts of expected returns. Analogously, if most of the variation in cap rate is driven by changes in expected return, the cap rate should be able to forecast future excess returns. This study explores whether commercial real estate yields are predictors of excess returns and if not, why not?

Previous research has identified that the relationship between cap rate and ex-post return does not always hold true. For example, using US data, Plazzi et al. (2010) find that cap rates can forecast expected returns for apartment, retail, and industrial properties, but not offices. Ghysels et al. (2007) show that cap rates can forecast returns in 16 out of 21 regions in the US. Lizieri et al. (2024) find that cap rates can weakly forecast capital returns for office and retail property, but not industrials in the UK. In addition, they showed poor out-of-sample forecasting power of cap rates. These results set the motivation for this study. What are the sources of forecast instability?

In this study, we demonstrate that forecast instability can be attributed to changes in the steady-state mean of cap rates over the sample period (i.e. change in the equilibrium cap rate). This indicates that the steady-state mean cap rate is subject to structural breaks. We define the adjusted cap rate as the deviation of the cap rate from its current steady-state mean. Utilising the shift in mean cap rate and adjusted cap rate, the in-sample forecasting power of the cap rate improves substantially. The adjusted cap rate can strongly forecast excess returns at 8-, 12-, 16 and 20-quarter horizons for office, retail and industrial properties in the UK.

In real time, however, the in-sample forecasting power is hard to exploit. In real time forecasting, an investor faces two main challenges. First, they must estimate the timing of a break. Second, if a new break is detected, they have to estimate the new mean cap rate after the break occurs. If this new break happens toward the end of the sample available to the investor, the new mean can only be estimated using a small number of observations, which leads to significant estimation uncertainty.

To evaluate these challenges, we conduct additional tests assessing the relative difficulty of estimating the break dates versus estimating the mean cap rate in real time. Our findings indicate that the real time estimation of the break dates is not crucial and the resulting prediction errors are small. In addition, we can detect the breaks with minimal delay, typically within nine quarters. Conversely, the estimation of the magnitude of the change in the mean cap rate after the break entails substantial uncertainty. To address the difficulty of estimating this new mean post-break, we define a transition period of five years following the break. During this period, we utilise the term structure of interest rates and the unemployment rate to determine the new mean of the cap rate. We show that the adjusted cap rate outperforms a random walk model (which uses historical average returns for prediction) for office and retail properties, but not for industrial properties. When applied to regional property indices, the adjusted cap rate outperforms the random walk model for most regional office and retail series. Notably, the adjusted cap rates outperform the unadjusted cap rate in out-of-sample forecasting in most cases. These results suggest that anyone seeking to use cap rates for forecasting and/or investment appraisal needs to: (1) test for structural breaks for cap rate; (2) utilise the adjusted cap rate (defined as the deviation of the cap rate from its current steady-state mean) following any break.[1]

This study contributes to the literature in three aspects. First, we provide more evidence on the information content of cap rates and their ability to forecast future excess return. Unlike previous studies (Ghysels et al, 2007; Plazzi et al., 2010) that largely focused on in-sample analysis, we provide a comprehensive evaluation of the cap rate's out-of-sample forecasting performance which is more useful for market participants. Second, this study identifies the sources of forecast instability and discusses the implication of structural breaks. In addition, we introduce an additional predictor for use in commercial real estate (CRE) forecasting, based on the deviation of the cap rate from its mean.[2] Previous studies have primarily relied on macroeconomic variables (Krysalogianni et al, 2004, Tsolacos et al., 2020); granular CRE indices (Van de Minne et al, 2002), sentiment (Dietzel et al., 2014; Beracha et al, 2019), real estate derivative prices (Bond and Mitchell, 2001), and surveys of market experts (McAllister et al., 2008; Papastamos et al., 2015; McAllister and Nase, 2020).

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[1] The steady-state mean cap rate changed after the break.
[2] Because the mean cap rate differs before and after the break, the deviation is used to capture the structural break effect.

The rest of the paper is organised as follows. Section 2 outlines the theoretical framework. Section 3 discusses the data and characteristics of cap rate. Section 4 presents findings for both in-sample and out-of-sample analysis. Section 5 discusses the investment implications of our findings and Section 6 summarises our conclusions.

2. Theoretical Framework

The total return (R_{t+1}) from holding a given commercial property from t to t+1 is:

$$1 + R_{t+1} = \frac{P_{t+1} + H_{t+1}}{P_t} \tag{1}$$

where P_{t+1} is the price of a commercial property at the end of period t+1 and $H_{t+1}$is the net operating income (net rent) of a commercial property from period t to t+1. The rent-to-price ratio H_t/P_t, known as the cap rate or yield, is analogous to the dividend-price ratio for stocks.

If we take log transformation and define $p_t = \log(P_t)$, $h_{t+1} = \log(H_{t+1})$ and $r_{t+1} = \log(1 + R_{t+1})$, following Campbell and Shiller's (1988) decomposition method, the present value log price of a CRE property is:

$$p_t = \frac{\kappa}{1-\rho} + E_t\left[\sum_{k=0}^{\infty} \rho^k [(1-\rho)h_{t+1+k} - r_{t+1+k}]\right] \tag{2}$$

κ and ρ are parameters derived from linearisation.[3] The pricing relation (2) indicates that the value of a CRE property is reflecting the expectation of future cash flows and expected returns (the required return, or discount rate). High property prices today reflect the expectation of high rental growth or low expected returns or both. The rent-to-price ratio H_t/P_t, known as the cap rate or yield, is analogous to the dividend-price ratio for stocks. If we define the log cap rate as $cap_t = h_t - p_t$, subtracting equation (2) from the current log rent, we get:

$$cap_t = -\frac{\kappa}{1-\rho} + E_t\left[\sum_{k=0}^{\infty} \rho^k r_{t+1+k}\right] - E_t\left[\sum_{k=0}^{\infty} \rho^k \Delta h_{t+1+k}\right] \tag{3}$$

One implication of equation (2) is that the cap rate should forecast future excess returns (the difference between total return and risk-free rate) or rental growth. If cap, r and Δh are at their steady-state $\overline{cap}$, $\overline{r}$, and $\overline{\Delta h}$. Equation (3) can be expressed as

$$\overline{cap} = \frac{\kappa}{1-\rho} + E_t\left[\sum_{k=0}^{\infty} \rho^k \overline{r}\right] - E_t\left[\sum_{k=0}^{\infty} \rho^k \overline{\Delta h}\right] \tag{4}$$

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3 In particular, $\rho = 1/(1 + \exp(\overline{h-p}))$, where $\overline{h-p}$ denotes the average log cap rate. κ is a constant of linearisation.

Subtract (4) from (3), we can express the variables in deviations from steady state:

$$cap_t - \overline{cap} = E_t\left[\sum_{k=0}^{\infty} \rho^k [r_{t+1+k} - \overline{r}]\right] - E_t\left[\sum_{k=0}^{\infty} \rho^k [\Delta h_{t+1+k} - \overline{\Delta h}]\right] \quad (5)$$

Defining the deviation from the steady state as "adjusted", the implication of equation (5) is that the adjusted cap rate should forecast adjusted future excess returns or adjusted rental growth.

3. Data

This study focuses on the three "traditional" commercial property sectors in the UK: office, retail, and industrial.[4] For each property type, we collect the equivalent yield (as a measure of the cap rate), the market rental value index, and total returns from MSCI.[5] We collect similar information for the regional property types. The data, available from 1987 at a monthly frequency, was converted to quarterly frequency. The yields of three-month Treasury bills and 10-year government bonds are from LSEG Workspace. The unemployment rate is from the Office for National Statistics.

Table 1 shows the characteristics of the cap rate. In this paper, we assume the cap rate is rational, meaning it is determined by rational expectations about future returns and rental growth. We acknowledge that the cap rate could be considered irrational if that underlying expectation is irrational. However, this study does not investigate whether the cap rate is driven by rational or irrational expectations.

The cap rate could be subject to structural breaks. A structural break is a sudden, fundamental, and permanent change in the steady state (i.e. the equilibrium cap rate). It is not a temporary fluctuation. A structural break in cap rate means that the historical relationship between net operating income (rental income) and market value, and the factors that influence them, has fundamentally changed. These breaks are typically caused by major, lasting shifts in the real estate market or the broader economy that permanently alter how investors value commercial property, such as fundamental changes in macroeconomic policies or significant sector-specific or technological changes. A

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[4] We focus on those three property sectors due to the availability of sufficiently long time series data. We acknowledge that alternative sectors have grown significantly in importance and now represent a large percentage of total capital allocated to UK commercial real estate.

[5] At June 2025, the market value of office, retail and industrial property on the monthly index was shown as £4.9billion, 5.2billion and £11billion respectively, making up 86% of the market cap of the properties in the index

structural change in the cap rate typically results in a significant shift in the rate's average level, allowing for visual identification.

To ensure a statistically rigorous and precise determination of the break dates, we first focused on adopting the Bai and Perron (1998) test. We also utilised the Pruned Exact Linear Time (PELT) algorithm and the Online Cumulative Sum (CUSUM) monitoring method. These methods yielded similar structural break dates; the pros and cons of using each are discussed in the following context.

To investigate whether the cap rate is subject to structural breaks, we use the Bai and Perron (1998) test. Ideally, we would use an unconstrained version of the test, which could determine the number of breaks. For example, we could test the null hypothesis of no break against the alternative hypothesis of one or two breaks with unknown break dates. However, we only have 37 years of data. In this scenario, the test tends to over-reject the null hypothesis, which could give an inaccurate measure of the number of breaks. Instead, we specify the number of breaks in the Bai and Perron (1998) framework and allow it to find the unknown break dates.

Panel A of Table 1 shows the break dates and the changes of mean log cap rate. For one break, the break date for office is Q4 2004 and the mean log cap rate decreased by -0.25 (196 basis points). The break date for retail is Q3 2003 for the mean log cap rate decreased by -0.16 (111 basis points). The break date for industrial is Q3 2014 and the mean log cap rate decreased by -0.47 (347 basis points).

For two breaks, the break dates for office are Q3 2004 and Q3 2014. The mean log cap rate decreased by -0.21 (168 basis points) and -0.08 (55 basis points) for those two breaks. The break dates for retail are Q2 2002 and Q4 2008. The mean log cap rate decreased by -0.25 (171 basis points) for the first break and increased by 0.12 (81 basis points) for the second break. The break dates for industrial are Q3 1999 and Q2 2015. The mean log cap rate decreased by -0.25 (234 basis points) and -0.37 (253 basis points) for those two breaks.

These results motivate us to construct an adjusted cap rate. However, whether we should utilise one or two breaks remains subject to further investigation. In the case of one break, we subtract the mean log cap rate from the cap rate. The adjusted cap rate with break date τ is calculated as follows:

$$\widetilde{cap_t} = \begin{cases} cap_t - \overline{cap_1} \text{ for t} = 1, \dots, \tau \\ cap_t - \overline{cap_2} \text{ for t} = \tau, \dots, \mathrm{T} \end{cases} \tag{6}$$

where $\overline{cap_1}$ is the sample mean of log cap rate before the break and $\overline{cap_2}$ is the sample mean of log cap rate after the break. We use the sample means as the estimates of the steady states of the cap rate. Similarly, we define the adjusted cap rate in the two breaks case.

Panel B of Table 1 compares some properties of the unadjusted and adjusted cap rates. For office, the unadjusted cap rate is nonstationary. However, once structural breaks are used to adjust the cap rate, it becomes stationary. The same applies to industrial. For retail, the unadjusted cap rate is already stationary and remains so after adjustment. Notably, the volatility of the adjusted cap rates is substantially lower than that of the unadjusted ones. Most of this decrease in volatility occurs between the "no break" and "one break" adjustments.

Table 1: Characteristics of cap rates

Panel A			
Property Type	Numbers of Breaks	Date(s)	$\Delta\overline{cap}$
Office	1	Q4 2004	-0.25
Office	2	Q3 2004, Q3 2014	-0.21,-0.08
Retail	1	Q3 2003	-0.16
Retail	2	Q2 2002, Q4 2008	-0.25, 0.12
Industrial	1	Q3 2014	-0.47
Industrial	2	Q3 1999, Q2 2015	-0.25, -0.37
Panel B			
Property Type	Numbers of Breaks	Stationary	Standard Deviation
Office	0	No	0.17
Office	1	Yes	0.11
Office	2	Yes	0.10
Retail	0	Yes	0.14
Retail	1	Yes	0.11
Retail	2	Yes	0.10
Industrial	0	No	0.26
Industrial	1	Yes	0.15
Industrial	2	Yes	0.11

4. Empirical Results

4.1 In-Sample Regressions

We run the following in-sample forecasting regressions at 4-, 8-, 12-, 16- and 20-quarter horizon:

$$y_{t+h} = \alpha + \beta cap_t + \varepsilon_{t+h} \tag{7}$$

where y is either log excess return or log rental growth rate. $y_{t+h} = \sum_{i=1}^{h} y_{t+i}$. We define the difference between total return and risk-free rate, $\log(1 + R_{t+1}) - \log(1 + RF_t)$, as excess return from t to t+1. RF_t is the risk-free rate from t to t+1. The annualised risk-free rate is proxied by the yield of a three-month Treasury bill. When h > 1, the standard error and the associated t-statistics can be biased due to the use of overlapping observations (Goetzmann and Jorion 1993; Nelson and Kim 1993; Jiang et al. 2019). To address this issue, we compute bootstrap standard errors using a circular block bootstrap. This method resamples the data in blocks of consecutive observations, effectively reproducing serial correlation and other dependencies.

Table 2 reports the in-sample regression results. Using unadjusted cap rate (no break), cap rate fails to forecast future excess returns in the short-run (4-quarter). This is consistent with the stock market literature that dividend yield has stronger return forecasting power for longer horizons (Cochrane, 1992).

For office properties, at 8-, 12-, 16-, and 20-quarter forecasting horizons, the unadjusted cap rate fails to forecast future excess returns. However, when using the adjusted cap rate with one break, the t-values increase substantially, and the coefficients become significant. The R-squared also shows a substantial increase. For two breaks, the t-values decrease and R-squared is only marginally increased compared to the one break case. This suggests that the one break model is the best fit for office properties.

For retail properties, at 8-, 12-, 16-, and 20-quarter forecasting horizons, the unadjusted cap rate can forecast future excess returns. However, using the adjusted cap rate with one break significantly improves the model, with both the t-values and R-squared increasing. For a model with two breaks, both the t-value and R-squared decreased compared to the one-break case. This indicates that the one-break model is the best fit for retail properties.

For industrial properties, at 4-. 8-, 12-, 16- and 20-quarter forecasting horizon, there is no evidence that the cap rate can forecast future excess returns when considering no breaks or one break. However, once two breaks are considered, the t-values increase substantially and the coefficients become significant. The R-squared also shows a substantial increase. This suggests that the two-break model is the best fit for industrial properties.

These results formed the initial motivation for our study. Theoretically, the cap rate should be able to forecast future returns, yet empirical results have often failed to provide supporting evidence. Our findings demonstrate that once structural breaks are considered, the adjusted cap rate gains the ability to forecast future excess returns. Furthermore, the cap rate for retail properties is stationary and exhibits forecasting power for future excess returns even without considering structural breaks. This evidence strongly suggests that the inconsistency between theoretical expectations and empirical results stems from the nonstationary nature of the cap rate, emphasising the critical need to account for structural breaks in forecasting models.

Given that the cap rate is theoretically expected to forecast excess returns, we use excess return as our primary outcome variable. The results for total returns are detailed in the Appendix.

Regarding rental growth, for all three property types, the cap rate only forecasts rental growth in the short-run (four quarters) once appropriate breaks are considered. Similar to the results for forecasting excess returns, the cap rate can forecast rental growth when two breaks are considered for industrial properties. For longer forecasting horizons, the cap rate failed to forecast rental growth.

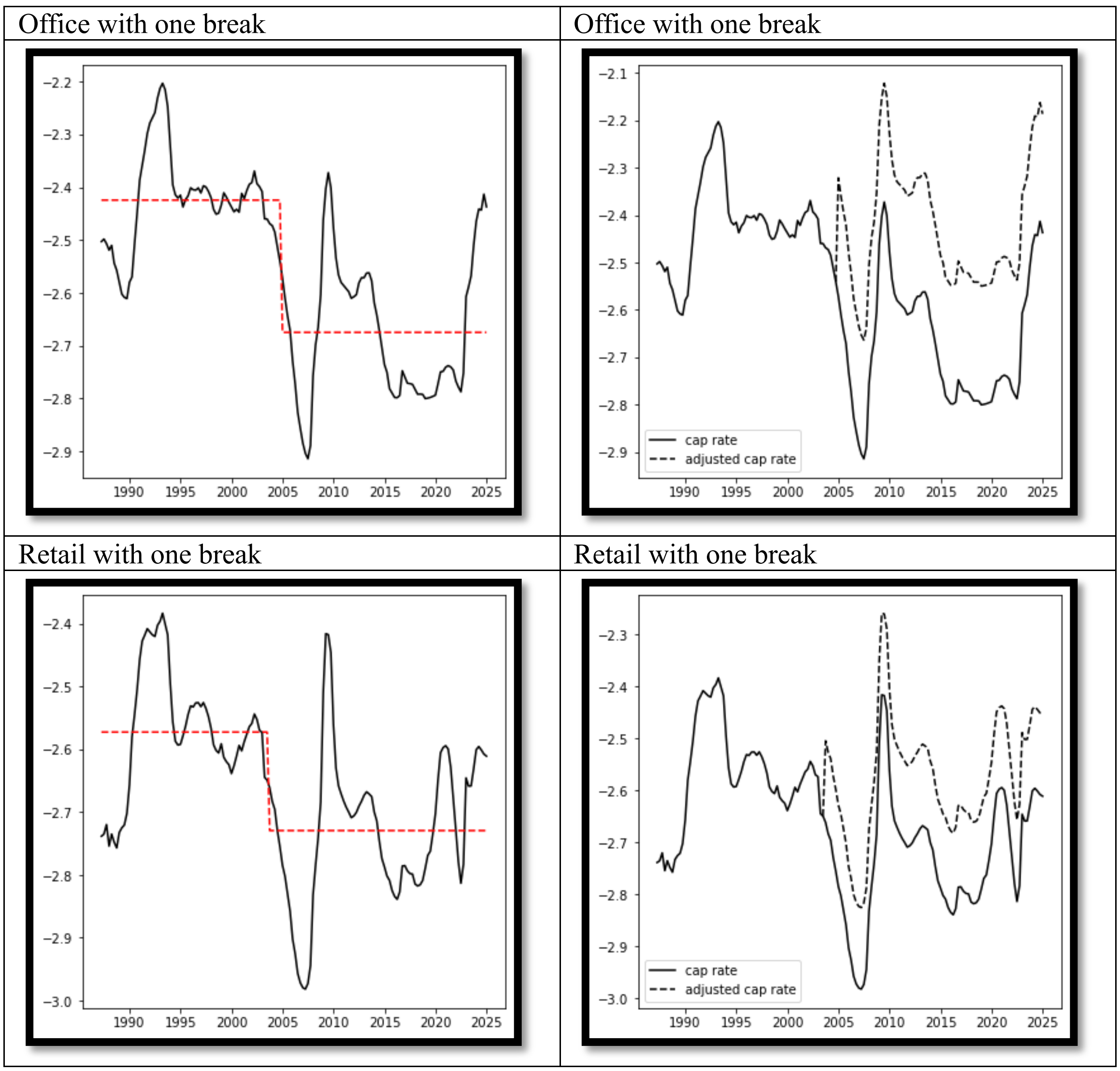
Table 2: In-sample regression

Property Type	Horizon	Statistics	Excess return			Rental growth		
			No break	One Break	Two Breaks	No break	One Break	Two Breaks
Office	4	Coefficient	0.05	0.17	0.16	-0.15	-0.36	-0.40
		t-value	0.42	1.04	0.76	-1.48	-2.63	-2.87
		R^2	0.53	2.10	1.72	10.61	23.69	25.69
Office	8	Coefficient	0.29	0.83	0.93	-0.19	-0.40	-0.46
		t-value	1.12	2.94	2.74	-1.01	-1.52	-1.53
		R^2	5.46	17.74	18.98	5.17	9.27	10.49
Office	12	Coefficient	0.39	1.17	1.34	-0.15	-0.22	-0.24
		t-value	1.29	3.22	3.15	-0.65	-0.73	-0.66
		R^2	7.08	25.53	28.31	2.11	1.83	1.84
Office	16	Coefficient	0.41	1.39	1.50	-0.10	-0.01	0.01
		t-value	1.31	3.25	2.92	-0.43	-0.04	0.01
		R^2	6.42	29.78	29.80	0.77	0.01	0.00
Office	20	Coefficient	0.44	1.75	1.78	-0.05	0.25	0.27
		t-value	1.39	3.88	3.26	-0.22	0.85	0.76
		R^2	6.13	40.93	36.72	0.17	1.93	1.92
Retail	4	Coefficient	0.21	0.30	0.28	-0.05	-0.24	-0.23
		t-value	1.49	2.18	2.23	-0.77	-2.61	-2.16
		R^2	6.93	8.81	6.69	2.08	28.56	22.31
Retail	8	Coefficient	0.60	0.88	0.88	-0.01	-0.32	-0.29
		t-value	2.38	3.68	3.50	-0.06	-1.80	-1.48
		R^2	22.42	29.82	26.19	0.02	15.82	11.64
Retail	12	Coefficient	0.85	1.19	1.17	0.11	-0.26	-0.22
		t-value	3.03	4.23	4.14	0.60	-1.12	-0.85
		R^2	32.25	40.05	33.94	1.80	6.35	4.03
Retail	16	Coefficient	1.00	1.29	1.19	0.27	-0.14	-0.09
		t-value	3.49	4.77	4.86	1.27	-0.53	-0.30
		R^2	37.95	40.23	29.71	8.11	1.29	0.45
Retail	20	Coefficient	1.11	1.40	1.17	0.45	0.02	0.07
		t-value	3.80	4.91	3.40	1.91	0.08	0.23
		R^2	42.87	41.66	26.01	18.36	0.03	0.23
Industrial	4	Coefficient	0.02	0.23	0.41	-0.06	-0.03	-0.15
		t-value	0.24	1.45	2.79	-1.35	-0.35	-1.67
		R^2	0.27	8.28	13.87	7.33	0.69	8.64
Industrial	8	Coefficient	0.06	0.47	0.97	-0.11	-0.03	-0.21
		t-value	0.31	1.65	3.74	-1.29	-0.16	-1.31
		R^2	0.65	15.45	33.54	7.08	0.17	5.02
Industrial	12	Coefficient	-0.05	0.49	1.15	-0.16	0.01	-0.17
		t-value	-0.20	1.25	3.37	-1.36	0.06	-0.73
		R^2	0.32	11.91	32.82	8.16	0.03	1.74

Industrial	16	Coefficient	-0.16	0.45	1.23	-0.20	0.08	-0.01
		t-value	-0.49	0.91	3.12	-1.28	0.28	-0.05
		R^2	2.07	7.57	27.10	8.69	0.67	0.01
Industrial	20	Coefficient	-0.17	0.44	1.33	-0.22	0.12	0.11
		t-value	-0.46	0.83	3.71	-1.23	0.41	0.43
		R^2	1.84	5.97	25.42	9.79	1.40	0.60

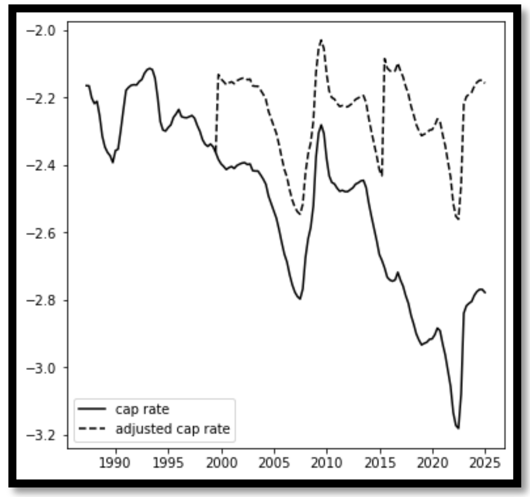
Given that the in-sample regression results show that one break is optimal for office and retail and two breaks are optimal for industrial, we plot the cap rates for comparison in Figure 1. In the left panels, we plot log cap rate alongside the mean log cap rate. Visually, we observe evidence of nonstationary. Cap rates are decreasing, particularly for industrial property. The right panel compares unadjusted cap rate and adjusted cap rate. Once the cap rate is adjusted, the series become stationary.

Figure 1: Cap rates with structural breaks



Industrial with two breaks

Industrial with two breaks



Based on the theoretical framework, a break in $\overline{cap}$ (average cap rate) must be associated with a change in $\bar{r}$ (average total return) or in $\overline{\Delta h}$ (average rental growth rate). First, we assume that $\overline{\Delta h}$ is constant and focus on changes in expected total returns. The change in $\bar{r}$ implied by the change in $\overline{Cap}$ can be inferred from $\overline{r_t} = \left(1 + \overline{\Delta h}\right) \exp(\overline{cap_t}) + \overline{\Delta h}$. Second, we assume $\bar{r}$ is constant and focus on changes in expected rental growth rate. The change in $\overline{\Delta h}$ implied by change in $\overline{Cap}$ can be inferred from $\overline{\Delta h_t} = (\bar{r} - \exp(\overline{cap_t}))/(1 + \exp(\overline{cap_t}))$.[6]

Table 3 reports the results. For office properties, the observed change in $\overline{cap}$ implies a decline in mean expected total returns of 2.00%, or an increase in mean expected rental growth rate of 1.84%. Although we observed a decline in total returns, this is mainly contributed by the decline of the risk-free rate: the excess return has actually increased. Similarly, the rental growth rate has decreased.

For retail properties, the observed change in $\overline{cap}$ implies a decline in mean expected total returns of 1.16%, or an increase in mean expected rental growth rate of 1.06%. As with office properties, the observed decline in total returns is largely attributable to a fall in the risk-free rate (excess returns have increased) and rental growth falls.

Industrial properties show more complex results. For the first break, the observed change in $\overline{cap}$ implies a decline in mean expected total returns of 2.41%, or an increase in mean expected rental growth rate of 2.21%. A decline in total returns was observed, largely due to the falling risk-free rate, while excess returns increased. The rental growth rate, however, decreased. After the second break, the observed change in $\overline{cap}$ implies a decline in mean expected total returns of 2.55%, or an increase in mean expected rental growth

[6] The proofs are in Appendix E.

rate of 2.40%. Although the risk-free rate had declined, excess returns increased substantially. Notably, the rental growth rate increased by 4.58%, which is a significantly higher rise than the implied rate. This may be a short to medium term adjustment before it normalises but has led to a period of higher returns.[7]

Based on the results reported in Table 3, we can conclude that the decline of $\overline{cap}$ for office, retail and the first break of industrial properties is mainly driven by the decline in the risk-free rate. The decline of $\overline{cap}$ for the second break in industrial markets is mainly driven by increase in rental growth, which may be due to a structural change in the demand for industrial (logistics) properties.

Table 3: Implied changes in mean expected returns and rental growth

	Office Break 1	Retail Break 1	Industrial Break 1	Industrial Break 2
Change in $\overline{Cap}$	-0.25	-0.16	-0.25	-0.37
Implied changes				
Implied change in expected total returns	-2.00%	-1.16%	-2.41%	-2.55%
Implied change in rental growth	1.84%	1.06%	2.21%	2.40%
Actual changes				
Actual change in total return	-4.72%	-5.94%	-4.30%	1.59%
Actual change in excess return	0.83%	-0.25%	1.15%	3.35%
Actual change in risk-free rate	-5.54%	-5.49%	-5.49%	-1.59%
Actual change in rental growth	-0.18%	-5.00%	-2.32%	4.58%

4.2 Out-of-sample predictability

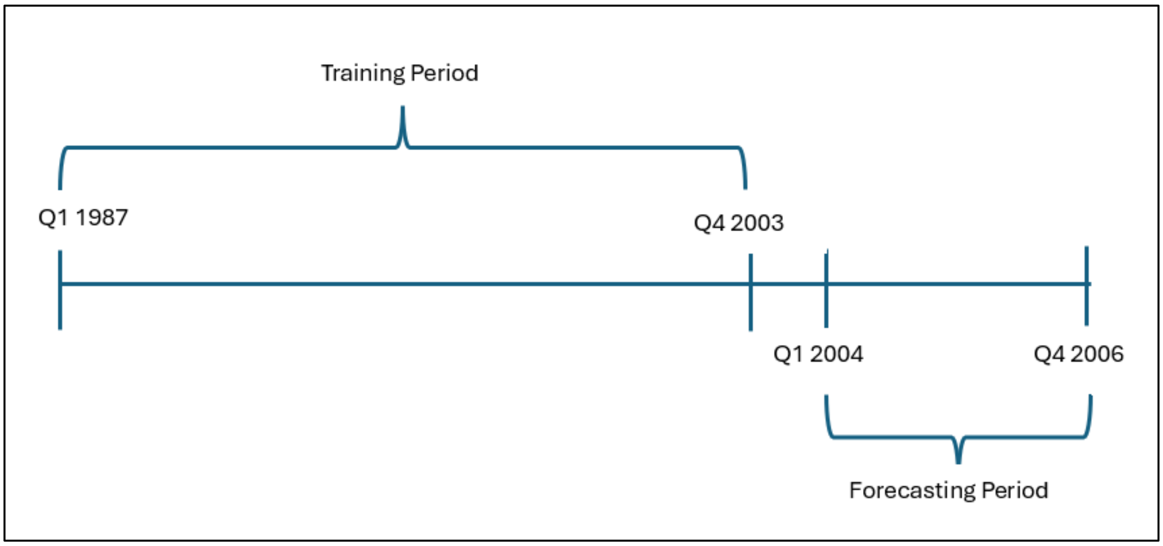
For the in-sample predictability analysis, we constructed adjusted cap rate based on the entire data sample. In this section, we investigate whether an investor, forming an adjusted cap rate in real time, would be able to predict out-of-sample returns. We focus on forecasting for a three-year horizon in this section (results of the five-year horizon are reported in Appendix F). Given the illiquidity and high transaction cost associated with CRE, a shorter time forecasting horizon would not be of practical benefit to investors. At any given time period t, we run the following regression of future cumulative excess return on cap rate using the training dataset:

$$ER_{t+h} = \alpha + \beta cap_t + \varepsilon_{t+h} \tag{8}$$

[7] We note our earlier comment that sentiment rather than rationality may play a role in short run market performance.

To ensure that we do not use future information in our predictions, all of the variables in our training dataset stop one quarter before the start of the forecasting period. For example, as demonstrated in Figure 2, if we are forecasting the cumulative excess return from Q1 2004 to Q4 2006, the variables in our training dataset would end at Q4 2000. Once the parameters of our forecasting model are estimated, we then use the cap rate in Q4 2003 as our input for the estimated model to forecast the cumulative excess return from Q1 2004 to Q4 2006.

Figure 2: Forecasting method



We start with 72 quarters of data, then we use recursive estimation with an expanding window. For every run, we add an extra quarter of information to re-estimate equation (8), and the forecast date moves one quarter later. During the whole process, we do not use information beyond the point of the forecasting date.

To evaluate the forecasting power of adjusted cap rate, we use several benchmarks. The first benchmark employs the historical average excess return for forecasting. The second uses the unadjusted cap rate. In real time forecasting, an investor faces two main challenges. First, they must estimate the timing of a break. Second, if a new break is detected, they have to estimate the new mean after the break occurs. If this new break happens toward the end of the sample available to the investor, the new mean can only be estimated using a small number of observations, which leads to significant estimation uncertainty. To investigate which of these issues is responsible for the deterioration of out-of-sample forecasting power, we consider two additional cases. In the first case, the investor knows the break dates and the *ex-post* mean value of the cap rate.[8] In the second case, the investor does not know the break dates but knows the *ex-post* mean value of the

[8] Although the break dates and ex-post mean are estimated using the full sample, the model estimation itself uses only the historical information available at any given point in time.

cap rate. In essence, we provide the investor with information about break dates and means from the entire sample. While these are not pure out-of-sample tests, they establish an informative benchmark for analysing the pure out-of-sample forecasts.

To evaluate the performance of out-of-sample forecasts, we use two standard metrics: mean absolute error (MAE) and root mean-squared forecasting error (RMSE). These are calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{10}$$

where y_i represents the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data points. MAE calculates the absolute difference between actual and predicted values, thus it assigns equal weights to all errors. However, RMSE penalises large errors more heavily, due to the squaring effect.

Based on Figure 1, the cap rates across the three property sectors exhibit distinct characteristics. The office cap rate is not stationary and shows a moderate downward shift over time. In contrast, the retail cap rate appears stationary, though it shifts slightly downwards over time. The industrial cap rate, however, is non-stationary and demonstrates a massive downward shift. These differing time series characteristics provide a valuable opportunity to test the forecasting power of adjusted cap rates within each unique scenario.

Table 4 presents the out-of-sample forecasting errors, with Panel A, B, and C reporting the results for office, retail, and industrial properties, respectively. Comparing the first two rows of each panel, the historical average forecast generally performs better than using the unadjusted cap rate, with the exception of retail properties. As previously discussed, this is attributable to the nonstationary nature of the cap rate for office and industrial properties. The third row of each panel reports results for "Pseudo OOS Case 1," where the investor knows the break dates and the *ex-post* mean cap rate. In this scenario, the errors are substantially lower than those from historical average forecasting. Notably, the forecasting errors from using the adjusted cap rate are significantly lower than those from using the unadjusted cap rate. This provides strong evidence that the forecasting power of the cap rate increases significantly once structural breaks are considered.

A key challenge for return predictability lies in how quickly a model can identify breaks in real time; significant delays in detection can severely hinder forecasting performance.

Table 4: Out-of-sample forecasting error

Panel A: Office			
	Forecasting variable	Mean absolute error	Root mean-squared error
Benchmark 1	Historical average	0.2248	0.2738
Benchmark 2	Cap rate	0.2578	0.3013
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.1931	0.2154
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.1987	0.2215
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.2025	0.2367
Panel B: Retail			
Benchmark 1	Historical average	0.1718	0.2343
Benchmark 2	Cap rate	0.1451	0.1671
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.1344	0.1576
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.1276	0.1505
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.1342	0.1545
Panel C: Industrial			
Benchmark 1	Historical average	0.2360	0.2727
Benchmark 2	Cap rate	0.3140	0.3501
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.1517	0.2056
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.1970	0.2761
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.2791	0.3532

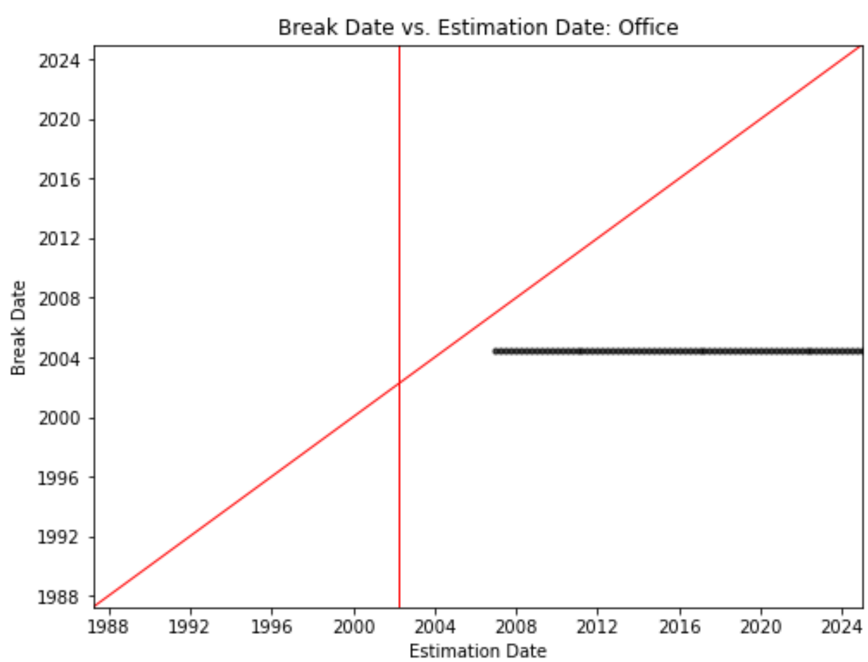
To explore this, Figures 3, 4, and 5 plot the break dates estimated in real time for office, retail, and industrial properties, respectively. The real time breakpoint detection works as follows: the initial model is estimated using the first 15 years of data. Then, the estimation window expands by one quarter at a time, and the model is re-estimated until it reaches the end of the sample, recording the break dates identified at each step. In the figures, the vertical line marks the first period at which the model is estimated, based on the initial 15-year training window (60 quarterly observations). The 45-degree line represents points where a break could be detected with zero delay. Black dots on the graph mark the break dates estimated in real time. The x-axis shows the estimation date, and the y-axis shows the estimated break dates. For example, if the estimation date is Q4

2006 and a structural break is detected in Q2 2004, we plot a black dot with an x-value of Q4 2006 and a y-value of Q2 2004. Once the first break is detected, we do not allow a second break within 10 years. We impose this constraint because commercial real estate cycles typically range from 9 to 20 years (Barras, 1994), and a new break within 10 years of the first might indicate a false alarm.

For office properties, the estimated break occurred in Q2 2004, with a detection date of Q4 2006, resulting in a 9-quarter delay. For retail, the estimated break was in Q2 2004, detected in Q3 2006, marking an 8-quarter delay. Industrial properties experienced two estimated breaks. The first, in Q1 1998, was detected in Q3 2002, leading to a 17-quarter delay. The second estimated break, in Q2 2014, was detected in Q3 2016, representing an 8-quarter delay. Overall, breaks were generally detected with minimal delay, with the notable exception of the first break in industrial property.

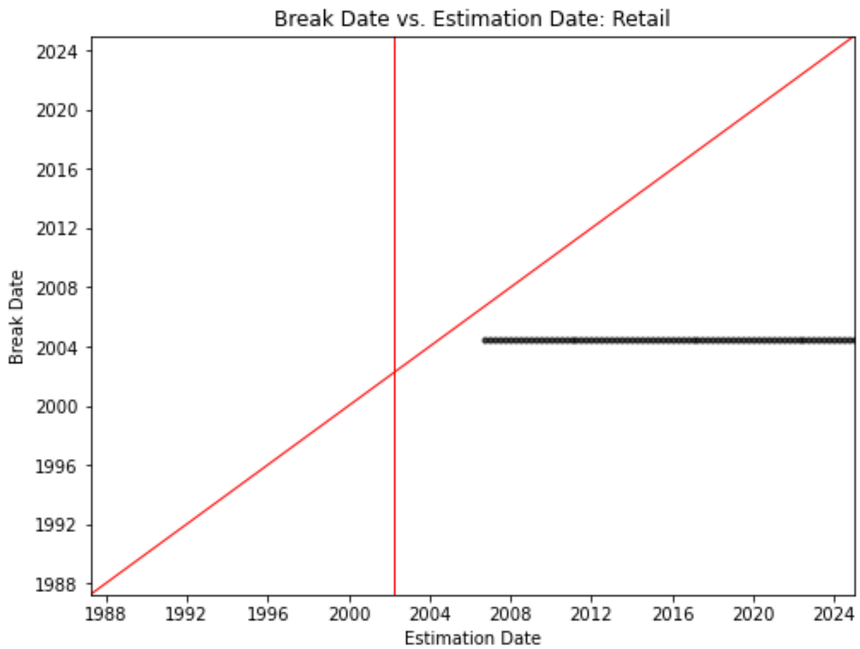
For real time break detection, we adopted the PELT algorithm, introduced by Killick et al. (2012). It is an efficient method for identifying multiple structural breaks within a time series. The benefit of choosing this algorithm is that we do not need to specify the number of breaks. PELT aims to find the optimal segmentation of a time series by minimising a penalised cost function. Thus, it automatically determines the number of breaks once the cost function is defined.

Figure 3: Recursively estimated break dates for office property



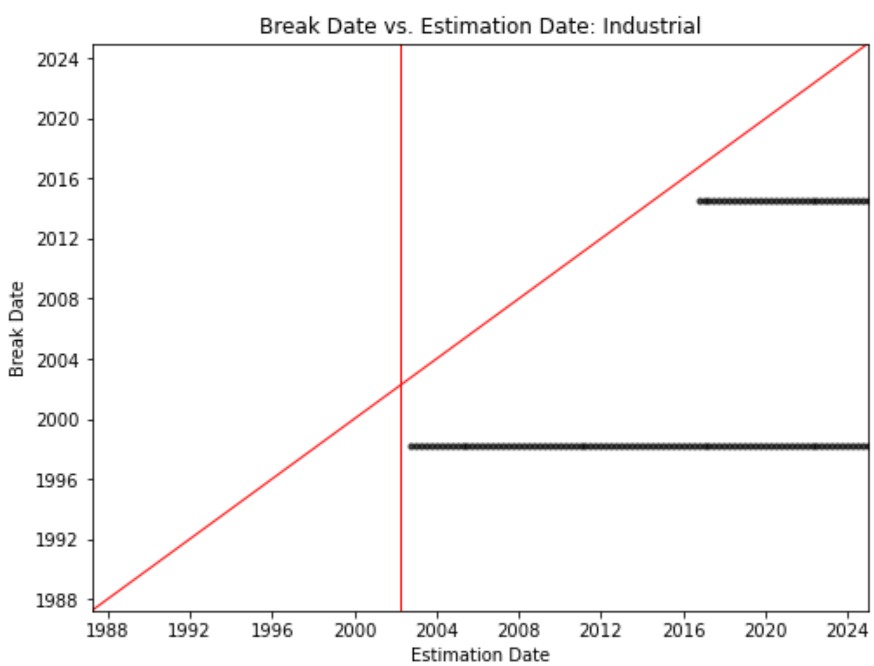
Note: The x-axis shows the estimation date (using historical information up to the estimation date). Black dots on the graph mark the break dates estimated.

Figure 4: Recursively estimated break dates for retail property



Note: The x-axis shows the estimation date (using historical information up to the estimation date). Black dots on the graph mark the break dates estimated.

Figure 5: Recursively estimated break dates for industrial property



Note: The x-axis shows the estimation date (using historical information up to the estimation date). Black dots on the graph mark the break dates estimated.

Alternatively, we could use the Bai and Perron (1998) test, which we utilised in our full-sample analysis. However, using this test with real time subsamples presents two primary challenges. First, as previously discussed regarding small sample sizes, this test is unreliable for determining the number of breaks: we need to specify the number of structural breaks *ex-ante*. For instance, if we consistently specified only one break, as with industrial properties, we would fail to identify the presence of two distinct breaks. Even if we define one break and use the first detected break as the primary, with subsequent shifts indicating a second, a second problem arises: in the case of industrial properties, the detection of the second break exhibits a significant time delay. The results of using the Bai and Perron (1998) test are plotted in Appendix C. We have specified one break, thus it always gives a break date for any subsample. For office properties, the initial break date is Q2 1990, with the break shifting to Q2 2004, detected with a five-quarter delay. For retail, the initial break is Q4 1989, shifting to Q3 2003, detected with a seven-quarter delay. For industrial, the initial break is Q4 1997, shifting to Q2 2014 with a substantial 28-quarter delay. Generally, this method can detect the first major break without significant delay, but the second break for industrial property shows a significant delay.

We also considered the CUSUM monitoring method, which is capable of detecting shifts in the mean in real time.[9] As shown in the Appendix D, using the first 10 years as the training set to establish target values, this method could detect breaks within a four-quarter delay for all three property types. However, a limitation of CUSUM is that it is not designed to detect multiple breaks. One potential avenue for improvement could involve combining all these individual models through an ensemble approach.

Once we defined the process for detecting breaks in real time, we performed an exercise for "Pseudo OOS Case 2". In this scenario, the investor estimates the break dates in real time but knows the *ex-post* mean cap rate. The results, reported in the fourth row of each panel, show that the adjusted cap rate still outperforms both the historical average forecasting and unadjusted cap rate forecasting. Given that we can detect breaks in real time without significant delay and the superior forecasting power compared to these two benchmark models, it appears that detecting breaks is not a major factor that would deteriorate forecasting performance.

Next, we conducted a pure out-of-sample analysis, where the investor estimates both the break dates and the *ex-post* mean in real time. Although we can detect breaks with minimal delay, we encounter another challenge: estimating the *ex-post* mean value is difficult due to the limited number of data points available immediately after a break. To

[9] The Online CUSUM monitoring method is a highly effective statistical process control technique used for online change detection—meaning it monitors a stream of data in real-time to quickly and sensitively detect a small, persistent shift in the mean of a process variable.

address this, we defined a transition period of five years following a break. Within this period, we determine the mean value of the cap rate by running a regression of the cap rate on a few state variables at each period. In Table 3, we show that the structural breaks in the cap rate for office and retail properties are mainly due to changes in the risk-free rate. Therefore, we use the term structure of interest rates and the unemployment rate to capture shifts in the economy's steady state and to form expectations about future interest rates. The term structure of interest rates is defined as the yield difference between the three-month Treasury bill and the 10-year government bond. For industrial properties, we add the annual changes of internet sales to total retail sales ratio, which could capture the demand for industrial properties. We then use the average of the predicted cap rate from the break point to the last observed data point as the mean cap rate. After this five-year transition period, we revert to using a simple average of the cap rate from the break point to the last observed data point.

The fifth row of each panel presents the results of the pure out-of-sample forecasting. For both office and retail properties, the adjusted cap rate forecasts continue to outperform both the historical average and unadjusted cap rate forecasts. However, for industrial properties, while the adjusted cap rate forecast still performs better than the unadjusted cap rate forecast, it falls short of the historical average forecast. Interestingly, the pure out-of-sample forecasting for retail is marginally superior to "Pseudo OOS Case 1". One of the reasons is that the real time detected structural break is slightly different from the break estimated using full sample (although only three quarters apart). These results suggest that if the cap rate is stationary, knowing the precise break date and *ex-post* mean cap rate might not be crucial. For office properties, which exhibit a modest shift in mean cap rate over time, the real time estimation still performs well. Conversely, for industrial properties, characterised by a substantial shift in mean cap rate over time, particularly with two breaks, the adjusted cap rate forecast is less accurate than the forecast using historical average, though it remains superior to the unadjusted cap rate forecast in terms of mean absolute error. Based on this analysis, it appears that the difficulty in accurately estimating the *ex-post* mean is the primary factor contributing to the increase in prediction errors in the pure out-of-sample scenario. The results for the five-year forecasting horizon show similar patterns and are reported in Appendix F.

The same pure out-of-sample forecasting process was applied to the property index at regional level in England. We only included indices with a full set of information as in the national index. This left us with 19 regional indices. For these regional studies, unemployment was defined as the unemployment rate specific to that region.

Table 5 presents the results. For offices, the adjusted cap rate forecasts better than the historical average, with the exception of London office. For retail, the adjusted cap rate outperforms the historical average. For industrial properties, the adjusted cap rate forecasts worse than the historical average. Across all regional results, except for some retail segments, the adjusted cap rate consistently forecasts better than the unadjusted cap rate.[10] This underscores the necessity of adjusting for structural breaks when using cap rates for forecasting. However, the challenge of accurately estimating the *ex-post* mean remains a persistent problem. The results for the five-year forecasting horizon show similar patterns and are reported in Appendix F.

Table 5: Regional out-of-sample forecasting error

Panel 1: London Retail			
	Forecasting variable	Mean absolute error	Root mean-squared error
Benchmark 1	Historical average	0.2029	0.2403
Benchmark 2	Cap rate	0.2117	0.2692
Pure OOS	Adjusted cap rate	0.1644	0.2048
Panel 2: London Office			
Benchmark 1	Historical average	0.2410	0.2930
Benchmark 2	Cap rate	0.2877	0.3570
Pure OOS	Adjusted cap rate	0.2548	0.2949
Panel 3: London Industrial			
Benchmark 1	Historical average	0.2533	0.2855
Benchmark 2	Cap rate	0.3274	0.3642
Pure OOS	Adjusted cap rate	0.2958	0.3654
Panel 4: South East – Retail			
Benchmark 1	Historical average	0.1779	0.2358
Benchmark 2	Cap rate	0.1735	0.2074
Pure OOS	Adjusted cap rate	0.1475	0.1832
Panel 5: South East – Office			
Benchmark 1	Historical average	0.2429	0.2949
Benchmark 2	Cap rate	0.2156	0.2602
Pure OOS	Adjusted cap rate	0.1875	0.2303
Panel 6: South East – Industrial			
Benchmark 1	Historical average	0.2445	0.2827
Benchmark 2	Cap rate	0.3269	0.3712
Pure OOS	Adjusted cap rate	0.2777	0.3379
Panel 7: South West – Retail			
Benchmark 1	Historical average	0.1718	0.2296
Benchmark 2	Cap rate	0.1301	0.1480
Pure OOS	Adjusted cap rate	0.1499	0.1857
Panel 8: South West – Office			
Benchmark 1	Historical average	0.2311	0.2815
Benchmark 2	Cap rate	0.2357	0.2860
Pure OOS	Adjusted cap rate	0.2302	0.2643
Panel 9: South West – Industrial			
Benchmark 1	Historical average	0.1989	0.2460
Benchmark 2	Cap rate	0.2530	0.2885
Pure OOS	Adjusted cap rate	0.2093	0.2505
Panel 10: Eastern – Retail			

[10] The cap rate for the retail sector tends to be stationary, and in this case, it may not be necessary to adjust it.

Benchmark 1	Historical average	0.1784	0.2488
Benchmark 2	Cap rate	0.1751	0.2099
Pure OOS	Adjusted cap rate	0.1472	0.1759
Panel 11: Eastern – Office			
Benchmark 1	Historical average	0.2330	0.2687
Benchmark 2	Cap rate	0.2246	0.2761
Pure OOS	Adjusted cap rate	0.2062	0.2411
Panel 12: Eastern – Industrial			
Benchmark 1	Historical average	0.2633	0.2973
Benchmark 2	Cap rate	0.3316	0.3751
Pure OOS	Adjusted cap rate	0.3230	0.4048
Panel 13: East Midlands – Retail			
Benchmark 1	Historical average	0.1620	0.2334
Benchmark 2	Cap rate	0.1533	0.2078
Pure OOS	Adjusted cap rate	0.1417	0.2042
Panel 14: East Midlands – Industrial			
Benchmark 1	Historical average	0.2057	0.2470
Benchmark 2	Cap rate	0.2704	0.3013
Pure OOS	Adjusted cap rate	0.2373	0.2885
Panel 15: West Midlands – Retail			
Benchmark 1	Historical average	0.1788	0.2409
Benchmark 2	Cap rate	0.1296	0.1556
Pure OOS	Adjusted cap rate	0.1382	0.1715
Panel 16: North West – Retail			
Benchmark 1	Historical average	0.1592	0.2326
Benchmark 2	Cap rate	0.1329	0.1570
Pure OOS	Adjusted cap rate	0.1326	0.1625
Panel 17: Yorks & Humber – Retail			
Benchmark 1	Historical average	0.1961	0.2753
Benchmark 2	Cap rate	0.1425	0.1718
Pure OOS	Adjusted cap rate	0.1971	0.2372
Panel 18: Yorks & Humber – Industrial			
Benchmark 1	Historical average	0.2070	0.2702
Benchmark 2	Cap rate	0.2582	0.3184
Pure OOS	Adjusted cap rate	0.2074	0.2484

5. Investment Implications

We first tested whether the cap rate could serve as an early warning indicator for the significant market downturn during the 2007-2009 Global Financial Crisis (GFC). To forecast these three years, we used information available until the end of 2006, specifically utilising the Q4 2006 cap rate to predict the cumulative excess return over the subsequent three years.

Table 6 presents these results. For both office and retail properties, the cap rate and the adjusted cap rate successfully forecasted at the end of 2006 a market downturn in subsequent years. However, given that the breaks for these sectors occurred in 2004, the estimated adjusted cap rate forecasts are subject to uncertainty due to the limited information available before 2006.

Industrial property provides a strong opportunity for this test, as its break occurred earlier, in 1998. For industrial, the unadjusted cap rate forecast was +16%, while the adjusted cap rate forecast was -31%. The actual cumulative excess return was -36%. Notably, all cap rate forecasts, both unadjusted and adjusted, outperformed the historical average forecasting method.

Table 6: Forecasting of cumulative excess return during 2007-2009

	Office	Retail	Industrial
Actual excess return	-42%	-45%	-36%
Historical average forecast	9%	12%	39%
Cap rate forecast	-46%	-22%	16%
Adjusted cap rate forecast	-35%	-13%	-31%

Next, we investigated whether the cap rate can be used for cross-sectional asset selection. To ensure a sufficient number of cross-sections, we utilised the regional property data. Given the mixed results from pure out-of-sample forecasting across different property types and regions, and the difficulty in accurately estimating the ex-post mean cap rate, we employed the actual break dates and historical means for this demonstration. This approach allows us to clearly illustrate the adjusted cap rate's performance in asset ranking.

For this analysis, we sorted all regional properties into quartiles based on either their unadjusted cap rate or adjusted cap rate. These portfolios were rebalanced every three years, and we tracked the equally weighted portfolio excess returns over a 21-year period.[11] We report the cumulative excess returns for each portfolio, alongside the cumulative excess return achieved by an equally weighted investment in all regional properties.

Table 7 presents these results. As we rebalance the portfolio every three years, we used three different starting years: 2001, 2002, and 2003. When using the unadjusted cap rate to rank and form portfolios, higher cap rate portfolios did not outperform lower cap rate portfolios. This contradicts the theory that higher cap rates should correspond to higher excess returns. However, once we used the adjusted cap rate to sort portfolios, a notable pattern emerged: higher adjusted cap rate portfolios consistently outperformed lower adjusted cap rate portfolios. Furthermore, the excess return of Portfolio 1 (highest adjusted cap rate) was better than an equally weighted investment across all regional

[11] Transaction costs are not included.

properties. We have also tried rebalancing the portfolio every five years; the patterns are similar.

Table 7: Cumulative excess returns of cap rate sorted portfolios using regional properties

	Portfolios				
Starting in 2001	1	2	3	4	Equally weighted all
Cap rate	93%	57%	105%	97%	89%
Adjusted cap rate	128%	93%	73%	58%	89%
Starting in 2002					
Cap rate	98%	50%	46%	101%	76%
Adjusted cap rate	133%	68%	62%	37%	76%
Starting in 2003					
Cap rate	62%	90%	40%	88%	70%
Adjusted cap rate	88%	83%	67%	45%	70%

6. Conclusion

This study addressed the inconsistent predictive power of cap rates in CRE. We found that structural breaks in the steady-state mean of cap rates are a key source of this forecast instability. Our core contribution is the development and application of an adjusted cap rate, defined as the deviation from this dynamic steady-state mean. This adjustment significantly enhanced in-sample forecasting power, enabling strong prediction of excess returns for UK office, retail, and industrial properties

Despite the challenges of estimating post-break mean changes in real time, the adjusted cap rate crucially outperformed both a random walk model and the unadjusted cap rate in out-of-sample forecasting for office and retail sectors. These findings highlight the importance of recognising that cap rates are prone to structural breaks and advocate for using the adjusted cap rate in CRE forecasting and asset selection. Future research should focus on developing better methods for detecting structural breaks and estimating the new steady-state mean in real time.

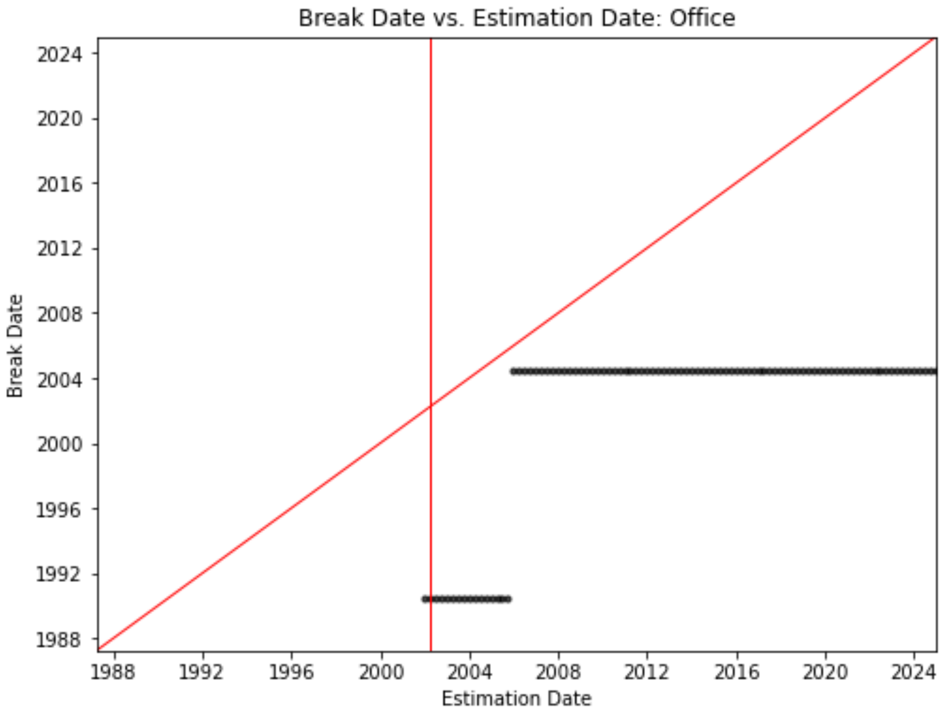
Appendix A: In-sample estimation of total return

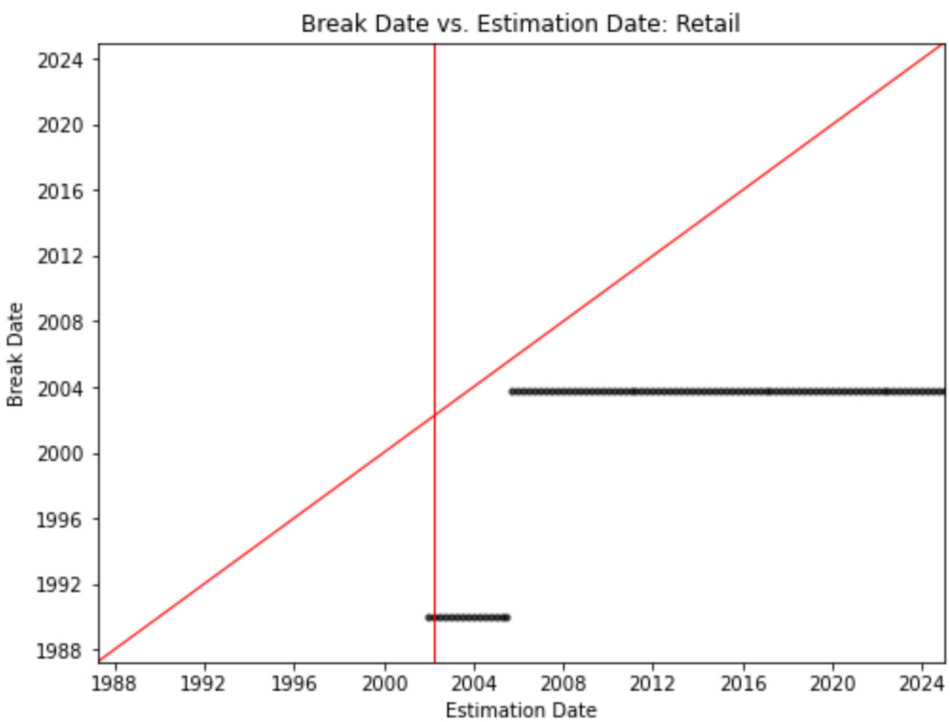
Property Type	Horizon	Statistics	Total return		
			No break	One Break	Two Breaks
Office	4	Coefficient	0.15	0.12	0.10
		t-value	1.38	0.77	0.49
		R^2	4.66	1.20	0.74
Office	8	Coefficient	0.47	0.70	0.78
		t-value	2.18	2.88	2.42
		R^2	17.03	14.83	15.26
Office	12	Coefficient	0.67	1.01	1.15
		t-value	2.75	3.67	3.47
		R^2	26.60	23.59	26.01
Office	16	Coefficient	0.80	1.19	1.30
		t-value	3.31	4.06	3.93
		R^2	33.76	30.78	31.31
Office	20	Coefficient	0.92	1.53	1.59
		t-value	4.01	5.11	4.53
		R^2	40.23	46.64	43.40
Retail	4	Coefficient	0.29	0.23	0.25
		t-value	2.43	1.60	1.72
		R^2	13.27	5.70	5.65
Retail	8	Coefficient	0.73	0.72	0.78
		t-value	3.63	2.63	2.76
		R^2	34.93	21.21	21.91
Retail	12	Coefficient	1.05	0.97	1.03
		t-value	4.77	2.77	3.03
		R^2	51.27	27.94	27.35
Retail	16	Coefficient	1.28	1.07	1.05
		t-value	5.45	3.18	3.51
		R^2	61.49	26.80	22.53
Retail	20	Coefficient	1.50	1.20	1.06
		t-value	5.43	3.59	2.83
		R^2	68.07	26.63	18.41
Industrial	4	Coefficient	0.11	0.30	0.37
		t-value	1.26	2.13	2.47
		R^2	5.78	16.29	12.85
Industrial	8	Coefficient	0.22	0.62	0.88
		t-value	1.35	2.53	3.31
		R^2	10.81	31.18	33.00
Industrial	12	Coefficient	0.22	0.74	1.04
		t-value	0.99	2.41	2.90
		R^2	8.04	36.09	35.84
Industrial	16	Coefficient	0.24	0.80	1.12
		t-value	0.86	2.19	2.65
		R^2	6.99	36.41	33.46
Industrial	20	Coefficient	0.32	0.90	1.26
		t-value	1.01	2.29	3.16
		R^2	9.72	37.74	34.97

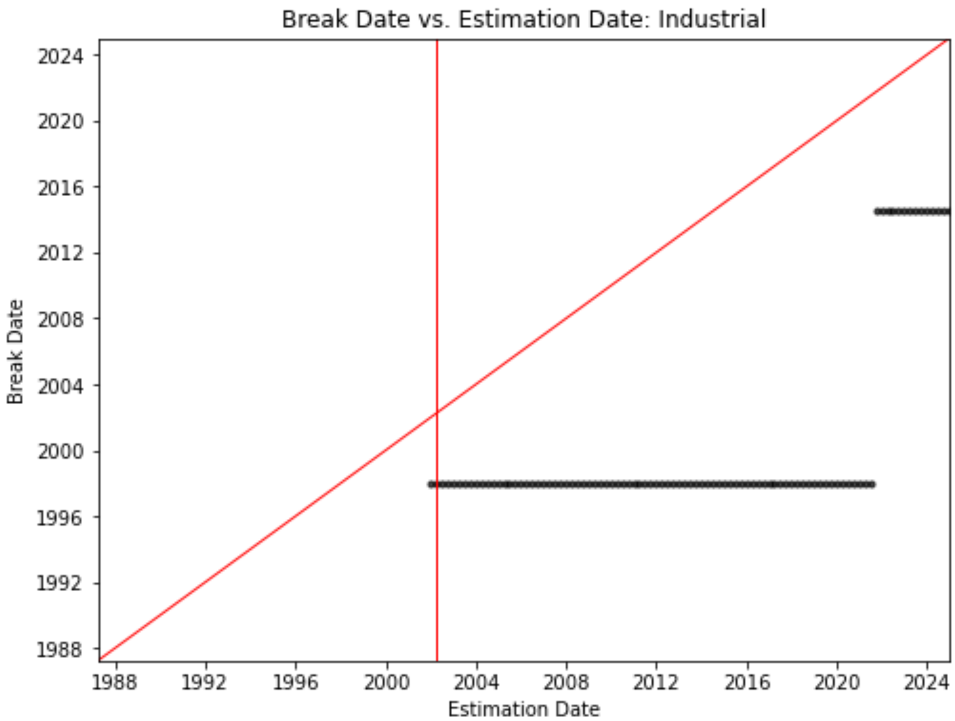
Appendix B: Out-of-sample forecasting error of total return

Panel A: Office			
	Forecasting variable	Mean absolute error	Root mean-squared error
Benchmark 1	Historical average	0.2111	0.2767
Benchmark 2	Cap rate	0.2022	0.2283
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.1858	0.2261
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.1848	0.2234
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.1793	0.2329
Panel B: Retail			
Benchmark 1	Historical average	0.2112	0.2864
Benchmark 2	Cap rate	0.1513	0.2001
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.1552	0.2036
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.1569	0.2125
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.2393	0.2939
Panel C: Industrial			
Benchmark 1	Historical average	0.1853	0.2577
Benchmark 2	Cap rate	0.2703	0.3152
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.1726	0.2161
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.2032	0.2482
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.2188	0.2506

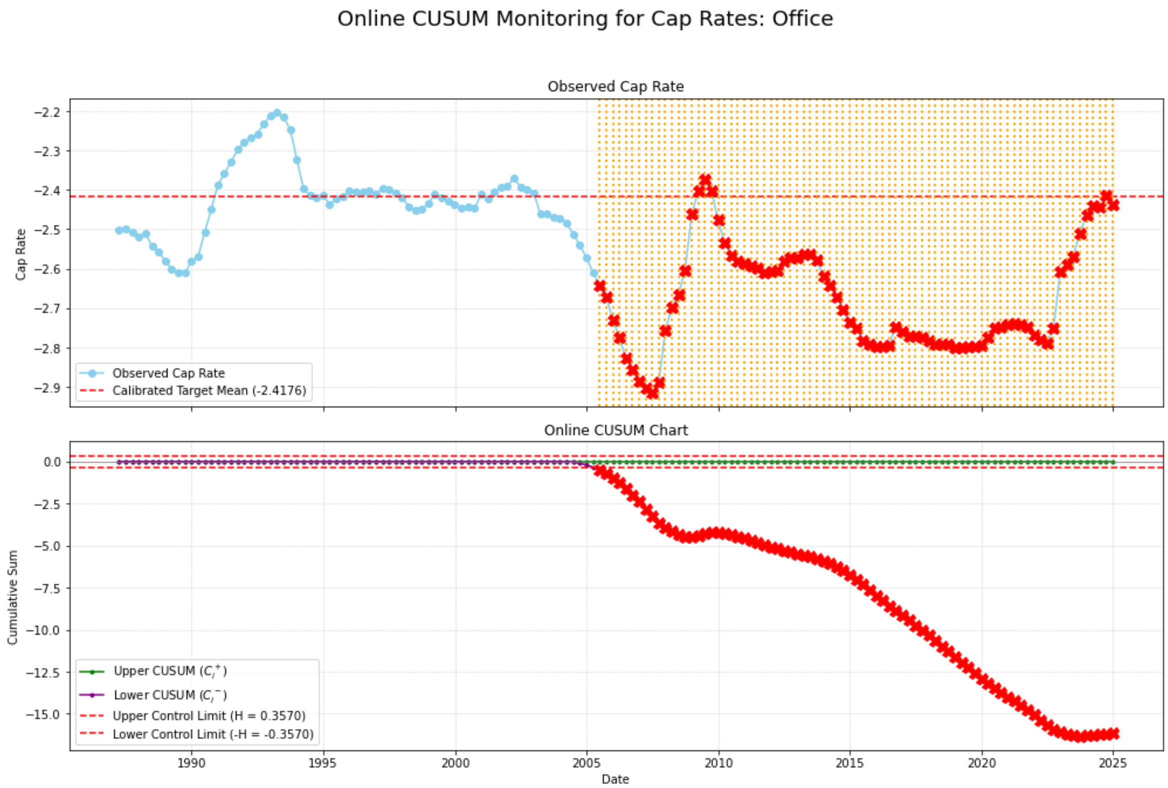
Appendix C: Recursively estimated break dates using the Bai and Perron (1998) test

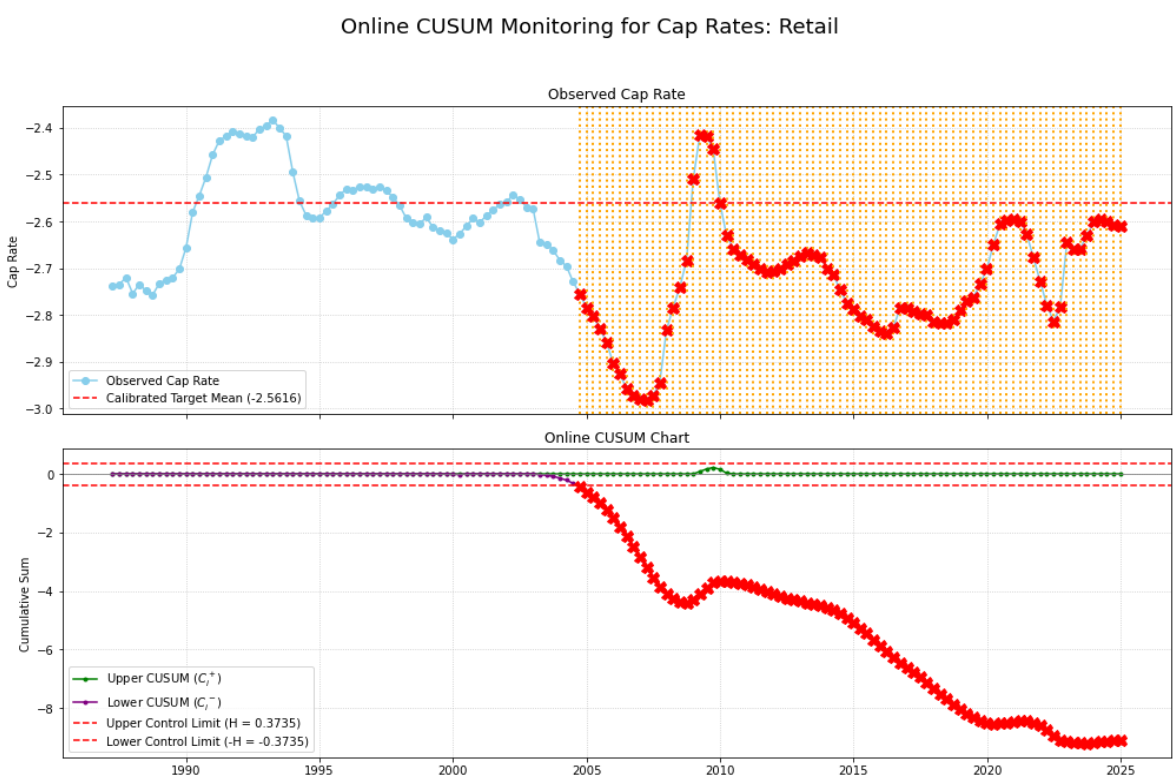




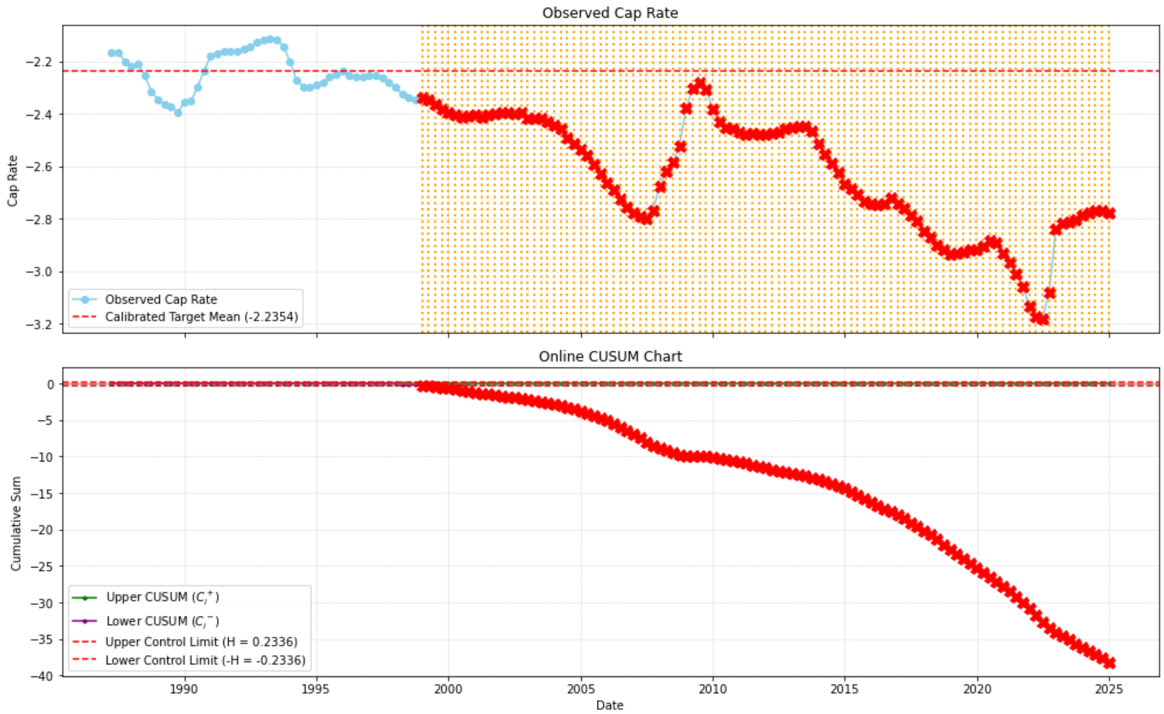

Break Date vs. Estimation Date: Industrial
Break Date
Estimation Date
2024
2020
2016
2012
2008
2004
2000
1996
1992
1988
1988
1992
1996
2000
2004
2008
2012
2016
2020
2024

Appendix D: Online CUSUM monitoring for cap rates





Online CUSUM Monitoring for Cap Rates: Industrial



Appendix E: Model for implied changes in total return and rental growth

Based on equation (1), the total return can be also defined as

$$1 + R_{t+1} = \frac{P_{t+1} + H_{t+1}}{P_t} = \frac{H_{t+1}}{H_t}\frac{1 + P_{t+1}/H_{t+1}}{P_t/H_t} \tag{E1}$$

As of period t, the steady-state growth rate of rent is $\overline{\Delta H_t}$ and steady-state of expected total returns are $\overline{R_t}$, implying a steady state for the cap rate:

$$\overline{CAP_t} = \frac{\overline{R_t} - \overline{\Delta H_t}}{\overline{\Delta H_t}} \tag{E2}$$

Take log on both sides:

$$\log(\overline{CAP_t}) = log\frac{\overline{R_t} - \overline{\Delta H_t}}{\overline{\Delta H_t}} \tag{E3}$$

Simplify, we get

$$\overline{cap_t} = \log\left(\exp(\overline{r_t}) - \exp\left(\overline{\Delta h_t}\right)\right) - \overline{\Delta h_t} \tag{E4}$$

Take exponentials on both sides:

$$\exp(\overline{cap_t}) = \frac{\exp(\overline{r_t}) - \exp\left(\overline{\Delta h_t}\right)}{\exp\left(\overline{\Delta h_t}\right)} \tag{E5}$$

Given that $\overline{r_t}$ and $\overline{\Delta h_t}$ are smaller than 1, we can approximate equation (E4)

$$\exp(\overline{cap_t}) = \frac{1 + \overline{r_t} - (1 + \overline{\Delta h_t})}{1 + \overline{\Delta h_t}} = \frac{\overline{r_t} - \overline{\Delta h_t}}{1 + \overline{\Delta h_t}} \tag{E6}$$

Appendix F: Out-of-sample forecasting error for five-year forecasting horizon

Table F1: Out-of-sample forecasting error with five-year forecasting horizon

Panel A: Office			
	Forecasting variable	Mean absolute error	Root mean-squared error
Benchmark 1	Historical average	0.3226	0.3697
Benchmark 2	Cap rate	0.4611	0.4994
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.2298	0.2595
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.2327	0.2619
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.3077	0.3305
Panel B: Retail			
Benchmark 1	Historical average	0.2231	0.2449
Benchmark 2	Cap rate	0.1413	0.1792
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.1156	0.1266
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.1120	0.1259
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.1082	0.1222
Panel C: Industrial			
Benchmark 1	Historical average	0.3395	0.3789
Benchmark 2	Cap rate	0.4908	0.5255
Pseudo OOS case 1: Know break dates and ex post mean cap rate	Adjusted cap rate	0.2515	0.3202
Pseudo OOS case 2: OSS estimate break dates, but know ex post mean cap rate	Adjusted cap rate	0.3201	0.4130
Pure OOS: OSS estimate break dates and mean cap rate	Adjusted cap rate	0.4330	0.5100

Table F2: Regional out-of-sample forecasting error with five-year forecasting horizon

Panel 1: London Retail			
	Forecasting variable	Mean absolute error	Root mean-squared error
Benchmark 1	Historical average	0.2763	0.3074
Benchmark 2	Cap rate	0.3651	0.4157
Pure OOS	Adjusted cap rate	0.2336	0.2721
Panel 2: London Office			
Benchmark 1	Historical average	0.3427	0.4106
Benchmark 2	Cap rate	0.5708	0.6329
Pure OOS	Adjusted cap rate	0.4537	0.5000
Panel 3: London Industrial			
Benchmark 1	Historical average	0.3713	0.4165
Benchmark 2	Cap rate	0.4747	0.5250
Pure OOS	Adjusted cap rate	0.4768	0.5564
Panel 4: South East - Retail			
Benchmark 1	Historical average	0.2281	0.2493
Benchmark 2	Cap rate	0.1776	0.2048
Pure OOS	Adjusted cap rate	0.1635	0.1729
Panel 5: South East - Office			
Benchmark 1	Historical average	0.3565	0.4007
Benchmark 2	Cap rate	0.3201	0.3499
Pure OOS	Adjusted cap rate	0.2465	0.2752
Panel 6: South East - Industrial			
Benchmark 1	Historical average	0.3634	0.4040
Benchmark 2	Cap rate	0.5021	0.5421
Pure OOS	Adjusted cap rate	0.4138	0.4925
Panel 7: South West - Retail			
Benchmark 1	Historical average	0.2155	0.2385
Benchmark 2	Cap rate	0.1429	0.1650
Pure OOS	Adjusted cap rate	0.1369	0.1882
Panel 8: South West - Office			
Benchmark 1	Historical average	0.3270	0.3600
Benchmark 2	Cap rate	0.3052	0.3635
Pure OOS	Adjusted cap rate	0.2498	0.3111
Panel 9: South West - Industrial			
Benchmark 1	Historical average	0.2715	0.3024
Benchmark 2	Cap rate	0.3839	0.4138
Pure OOS	Adjusted cap rate	0.3082	0.3510
Panel 10: Eastern - Retail			
Benchmark 1	Historical average	0.2051	0.2392
Benchmark 2	Cap rate	0.1648	0.2117
Pure OOS	Adjusted cap rate	0.1184	0.1286
Panel 11: Eastern - Office			
Benchmark 1	Historical average	0.3657	0.4035
Benchmark 2	Cap rate	0.4194	0.4522
Pure OOS	Adjusted cap rate	0.3112	0.3612
Panel 12: Eastern - Industrial			

Benchmark 1	Historical average	0.4035	0.4461
Benchmark 2	Cap rate	0.5509	0.6128
Pure OOS	Adjusted cap rate	0.5396	0.6112
Panel 13: East Midlands - Retail			
Benchmark 1	Historical average	0.1867	0.2178
Benchmark 2	Cap rate	0.1598	0.1891
Pure OOS	Adjusted cap rate	0.1508	0.1819
Panel 14: East Midlands - Industrial			
Benchmark 1	Historical average	0.2839	0.3259
Benchmark 2	Cap rate	0.4013	0.4382
Pure OOS	Adjusted cap rate	0.3848	0.4289
Panel 15: West Midlands - Retail			
Benchmark 1	Historical average	0.2355	0.2589
Benchmark 2	Cap rate	0.1214	0.1451
Pure OOS	Adjusted cap rate	0.1219	0.1722
Panel 16: North West - Retail			
Benchmark 1	Historical average	0.1867	0.2192
Benchmark 2	Cap rate	0.1211	0.1383
Pure OOS	Adjusted cap rate	0.1232	0.1521
Panel 17: Yorks & Humber - Retail			
Benchmark 1	Historical average	0.2471	0.2908
Benchmark 2	Cap rate	0.1437	0.1728
Pure OOS	Adjusted cap rate	0.2424	0.2732
Panel 18: Yorks & Humber - Industrial			
Benchmark 1	Historical average	0.2748	0.3179
Benchmark 2	Cap rate	0.4117	0.4423
Pure OOS	Adjusted cap rate	0.3191	0.3495

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RESEARCH

Investment Property Forum
R+ Building, 2 Blagrove Street,
Reading, Berkshire
RG1 1AZ

Email: ipfoffice@ipf.org.uk
Web: www.ipf.org.uk